DEMAND RESPONSE ASSESSMENT AND STRATEGY PLANNING FOR THE CONDOMINIUM RESIDENTIAL SECTOR IN JAPAN

A Thesis

by

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ABSTRACT

Dealing with peak electricity demand has always challenged electric power companies. Recent shrinkage of electricity supply capacity due to the nuclear accident in Fukushima, Japan, as well as growing electricity demand under extreme weather conditions threaten a shutdown of the electricity grid in the Kanto region of Japan. Demand response (DR) is one solution that reduces electricity consumption during those “tight” periods by 1) using incentives to solicit electricity consumers to cut consumption, or 2) raising real-time electricity prices.

The residential sector has become the new target for improving energy efficiency, and this research estimates the potential electricity demand reduction at peak hours based on ten minute interval historical electricity consumption data for Japanese households from July 2012 to September 2012 with 94 samples. A DR solution is considered where every electricity consumer in each house is assumed to i) leave the house, ii) cut consumption indoors, or iii) take no action in response to a predicted peak demand. The consumption levels reducible by actions i) and ii) are estimated, and simulations are run based on scenarios with different percentages of residents that take one of the three options. Of the three scenarios considered, the scenario “Medium Participation” highlights the most realistic level of DR outcome where 40% of residents in the house leave the house and 30% of the residents decide to reduce consumption indoors. This scenario is thought to be an ‘achievable’ level of DR outcomes, and our estimations show that, on average, the household electricity demand peak could be reduced by 28.6%. If the total demand peak for the residential sector in

TEPCO service areas could be reduced by 28.6%, then the peak reduction would be equivalent to the electricity supply capacity of 4 and one quarter of nuclear reactors.

Furthermore, living patterns of the households and their relationship with family structure is investigated, to answer the questions such as ‘Who consumes electricity during peak demand?’ or ‘What are the characteristics of those residents?’ The results of that investigation provide evidence that ties to recommendations aimed at designing effective DR programs for the residential sector. We first identified 4 representative living patterns based on the hours of resident occupancy. We found that on a daily basis, in an average of 46% of the households at least one household member remains in the house and consumes electricity during the day time. We identify this group of households to be a major potential contributor to DR programs. We then looked into the distribution of different family structures that characterize this group and found that nearly 70% of the households are couples living with their children.

These findings enable us to recommend actions plans for policy makers and grid operators. We then describe a number of suggestions that would help households in each of the categories to contribute towards DR. We also suggest how businesses could engage in this project by motivating families that are inside the house during peak demand hours to participate in DR programs. Because, we identified that the majority of the households in Kashiwa-no-ha that consume electricity during peak demand hours are families living with children, our proposals emphasize the importance of providing services to motivate these families to leave their houses during times of peak demand. The findings and recommendations stated in this research should help policy makers and grid operators to design more effective DR programs.

Key words: Demand Response, Residential Sector

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TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

LIST OF TABLES

LIST OF FIGURES

LIST OF FIGURES (continued)

LIST OF ABBREVIATIONS

CPP	Critical Peak Pricing
CT	Current Transmisson
DR	Demand Response
TEPCO	The Tokyo Electric Power Company
TOU	Time-of-use

LIST OF TERMS

e_{max}: The estimated maximum 60 minute interval power consumption (W) for the particular day of interest

e_{min}: The estimated minimum 60 minute interval power consumption (W) for the particular day of interest

e_{basic}: The 60 minute interval power consumption (W) a particular household consumes regularly when family members are actively consuming electricity

E_{norm}: Total energy consumption (Wh) per hour from regular consumption by an active family member in the house for a particular household between 10AM and 6PM

E_{shift}: Total energy consumption (Wh) per hour from temporal use of electricity by an active family member in the house for a particular household between 10AM and 6PM

E_{base}: Total energy consumption (Wh) per hour from base load consumption such as refrigerators for a particular household between 10AM and 6PM

E_{NORM}: Aggregate total energy consumption (kWh) per hour from the sum of all E_{norm} for the entire residential building

E_{SHIFT}: Aggregate total energy consumption (kWh) per hour from the sum of all E_{shift} for the entire residential building

l_{it}: A normalized value between 0 and 5 assigned to each 60 minute interval data for household i on time (hour) t

h_{it}: 10 minute interval energy consumption a particular household consumes as a result of a family member remaining inside a house for household i on time (10 minutes) t.

e_t: Actual 10 minute interval electricity consumption measurements (W) for household i on time (10 minutes) t.

LIST OF UNITS OF MEASUREMENT

GW	Gigawatt (unit of power)
kW	kilowatt (unit of power)
kWh	kilowatt hour (unit of energy)

Chapter 1 INTRODUCTION

1.1. Introduction

On March 11, 2011, a strong earthquake of magnitude 9.0 on the Richter scale suddenly hit the north eastern coast of Japan. The Tohoku coastal line was later hit by a series of strong tsunami waves damaging the Fukushima-Daiichi nuclear power stations in operation. The loss of cooling capacity of the reactors led to a series of devastating explosions releasing radioactive substances to the atmosphere. This event was not only life threatening to the people, but also a significant shock to the electricity dependent society. Rolling blackouts had followed to deal with the immediate loss of electricity supply capacity. The whole society began energy saving campaigns shifting working schedules for industries and dimming some lights in the public. Through this nuclear disaster, and the efforts made to cope with a new energy crisis, discussions on designing a more sustainable electricity system have emerged throughout the country.

Electricity demand peaks have always challenged power companies. After the recent nuclear disaster in Fukushima, Japan, the Tokyo Electric Power Company (TEPCO) lost a significant amount of its electricity supply capacity, which threatened its ability to meet the demand peaks in the following summer. Demand response (DR) is known as one solution to solve this issue. This research explores the potential of DR for condominium type residential sectors under the TEPCO's service areas. Historical electricity consumption data at 10 minute intervals from October, 2011 to September 2012 on 94 unified condominium sample houses in Kashiwa-no-ha, of Kashiwa City are analyzed to estimate the potential range of electricity reductions that could be attained using DR from these electricity consumers.

1.2. Overview

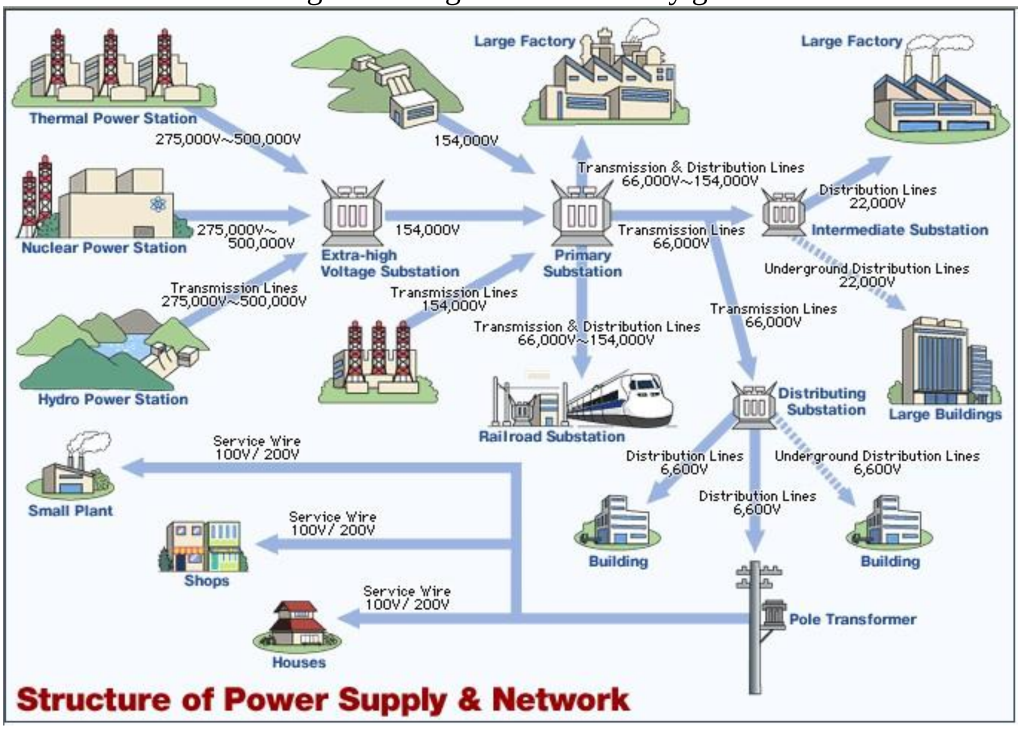
Chapter 1 provides a general background to electricity infrastructure as well as explaining the basic concept of peak demand and DR. Chapter 2 explains how the research will focus into residential electricity demand with research objectives to follow. Chapter 3 explains the type of data being used for analysis followed by the methodology for estimating DR potential. Chapter 4 explains results from estimations, and discussions are included in the final chapter.

Chapter 2 BACKGROUND

2.1. Basic Structure of an Electricity Grid

The fundamental principles of electricity infrastructure are described in this section. Figure 1 indicates a general view of a typical electricity infrastructure.

Figure 1 Image of an electricity grid



Source: [1]

Electricity is generated at power stations from a wide variety of energy sources, including coal, natural gas, nuclear fission, hydro, and more. Electricity is then delivered through a series of power cables to reach consumers demanding electricity for commercial, industrial, and residential purposes. Some power stations possess an enormous amount of output potential that is measured in units of giga watts (billions of watts). This scale enables them to achieve economies of scale. Electricity is delivered from centralized power stations through transmission lines at high voltage. The higher voltage enables power delivery with low energy loss and suits long distance delivery. Substations that are located closer to consumption areas lower the voltage so that electricity is formatted into each consumer's preference. Factories consume electricity at higher voltages that exceed 10,000 volts to operate heavy duty machinery. Homes or small shops prefer electricity at lower voltages because they rely on electronic appliances that operate at around 100 volts in Japan. The current Japanese electricity infrastructure is characterized by centralized monopoly suppliers, single direction of electricity flow, and large area coverage.

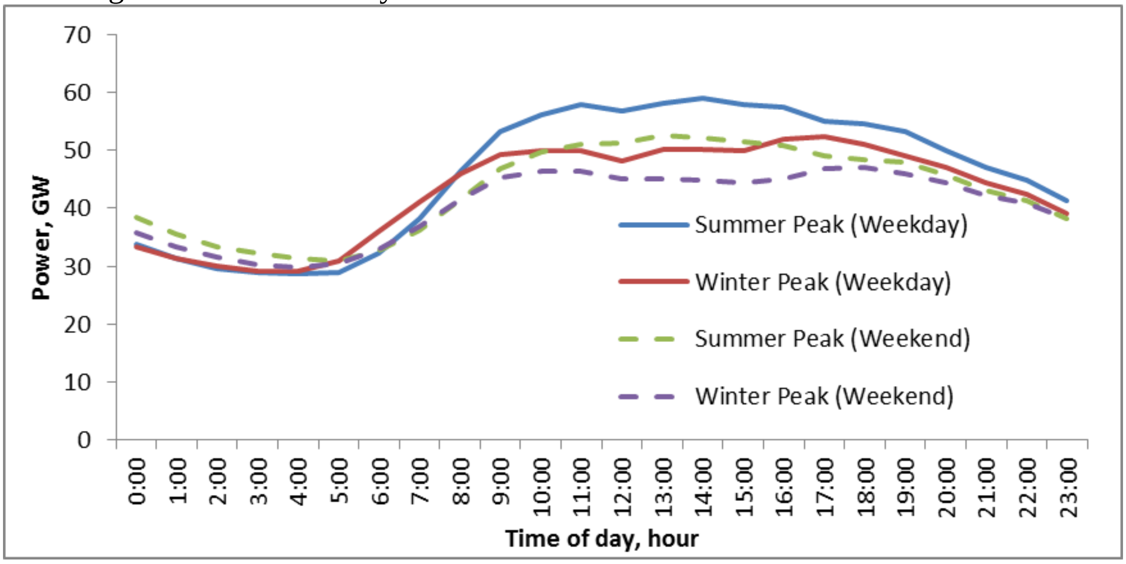
2.2. The Fundamental Principles of Electricity

Current economic and institutional barriers make it difficult and costly to store electricity [2]. Therefore, as a general rule, electricity demand and supply must always be balanced to provide continuous and reliable electricity service. This implies that electricity demand must never exceed total electricity supply capacity and power stations must never undersupply electricity demand. The moment the system faces disequilibrium of demand and supply, the entire system shuts down resulting in a power outage [3]. The current paradigm requires that the balance of demand and supply be maintained almost entirely by the supply side. Electricity demand dynamically fluctuates during the day requiring power suppliers to make constant adjustments to supply.

2.3. Determining Peak Electricity Demand

Electricity demand for a region fluctuates throughout the day. Depending on the characteristics of the region, electricity demand may reach daily peaks at different hours of the day. Under TEPCO's service areas, electricity demand fluctuates in a manner shown on figure 2.

Figure 2 Peak electricity demand in the summer/winter for TEPCO in 2010



Source: Recreated by author [4]

As shown in figure 2, for TEPCO, peak electricity demand is generally reached between 2PM to 4 PM on a hot summer day. When electricity demand reaches the lowest point of the day, the level drops to approximately 50% of the peak. This requires TEPCO to make wide ranges of supply adjustments.

This task of meeting the highest electricity demand has always challenged power companies. Power companies usually possess redundant supply capacity greater than the expected peak demand to assure their capacity of adjusting supply to demand fluctuations. Since power companies construct supply capacity to meet such acute peaks in the summer, they possess power plants that rarely operate throughout the entire year [5]. Power companies must bear the cost for maintaining these idle power plants and this large burden is usually reflected on electricity prices.

Electricity demand curves could depend on geographic location, climate, and composition of electricity consumers. Therefore, in other locations, demand peaks are possibly observed in different hours of the day. Extreme weather is the most common reason for high demand peaks, but there are other occasions such as power plant maintenances or damages caused on the electricity grid that hinder secure electricity supply. Failing to supply sufficient electricity will cause temporary power outages and destroy components of the electricity infrastructure that further threaten continued electricity service. A combination of extreme heat waves with damaged electricity grids could become a worst case scenario.

2.4. Consequences of Power Outages

One of the more recent power outages in the world occurred in India in the summer of 2012. This power outage was reported to be a result of overloading a huge network that stretched across three interrelated electricity grids covering a vast area stretching from the eastern coast to the borders of Pakistan. The power outage affected the daily lives of over 670 million people for over two days. Although, no casualties were reported, traffic jams, trapped coal miners, and stranded train passengers were notable consequences. This power outage was recorded as the largest power outage in terms of people affected. [6]

Power outages are also common in some of the most powerful countries in the world, the United States. In the summer of 2003, the great northeastern blackout affected the lives of over 50 million people in the northeastern states to parts of Canada. The power outage lasted nearly two days, severely affecting financial centers located in New York and Toronto and leaving a huge economic impact estimated between 7 to 14 billion US dollars. The cause of this power outage was again reported as a result of peak loading [7].

While the two cases reviewed here were due to excessive electricity loading, power outages can also occur as a result of damaged infrastructure. Perhaps one of the most devastating nuclear accidents in the 21st century occurred in Fukushima, Japan.

2.5. The Nuclear Disaster

On March 11, 2011, a strong earthquake with a magnitude of 9.0 on the Richter scale suddenly hit the north eastern coast of Japan. The Tohoku coastal line was later hit by a series of strong tsunami waves between 14 to 15 meters of height, which damaged the Fukushima-Daiichi nuclear power stations in operation [8]. After losing the ability to cool the reactors, the aftermath of this incident was beyond human imagination.

Soon after the disaster, TEPCO realized that it had a severe shortage of electricity supply to meet electricity demand, and they announced the need for a rolling blackout. Businesses and households took turns to experience temporary power outages and were forced to discontinue all activities during those hours to relieve stress on the electricity grid. This event indicated the need for a dramatic change in the Japanese electricity paradigm.

As an immediate response to electricity supply shortage, TEPCO announced and executed a rolling blackout. This action temporarily relieved tensions from increasing electricity demand on the electricity grid, but it was not a permanent solution. The damage caused to Fukushima and the vicinity by the radioactive pollution reaffirmed the risks involved with dependence on nuclear energy. The management of used nuclear reaction rods is also an unsolved problem that concerns the hearts of Japanese citizens. Ever since shutting down all nuclear power stations in Japan, continuing public protests as well as unsolved safety issues of operating nuclear power remain as great barriers for their recovery. As of October 2012, 53 out of 54 nuclear power plants are shut down, which significantly limits electricity supply capacity for all power companies in Japan [9].

2.6. How Power Companies Shall Deal with Peak Demand

At the discussion level, the way in which society must deal with peak demand is changing ever since the nuclear disaster in Fukushima in March, 2011. The conventional methodology was to raise supply capacity by constructing power plants to clear the highest peak electricity demand expected in one year. Prolonged public protests against continuation of nuclear power impede resumption of nuclear power plants. TEPCO currently intends to increase supply capacity by substituting the loss through recovering and building new power stations that rely more on fossil fuels.

Figure 3 Indication of how electricity supply meets electricity demand

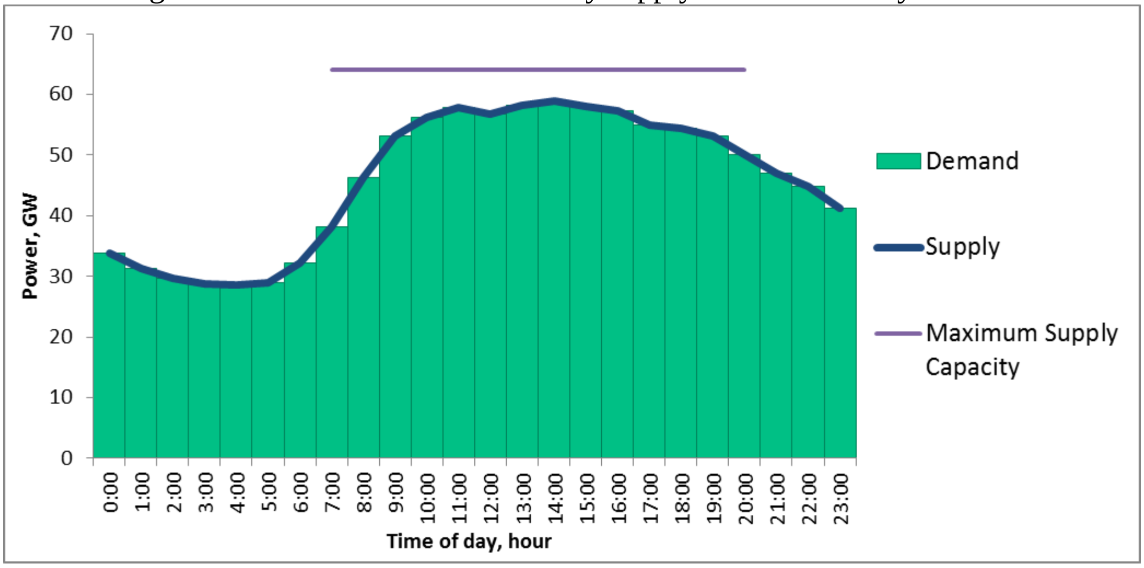


Chart created by author based on [4,10]

Limited electricity supply capacity becomes a problem when dealing with peak electricity demand as it limits the flexibility of power companies to comply with volatile electricity demand. Figure 4 indicates a case where electricity demand exceeds total supply capacity. A power outage to all service areas is possible in such cases [3].

Figure 4 Diagram of electricity demand exceeding supply capacity

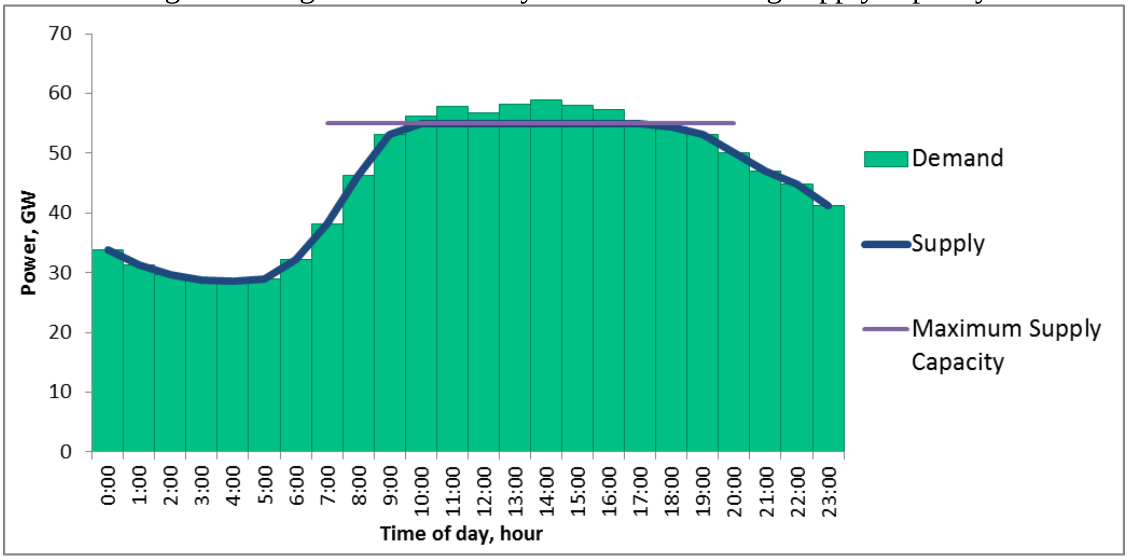


Chart created by author based on [4,10]

2.7. Use of DR

DR is a tool used by power companies whereby electricity consumers are requested to reduce electricity consumption whenever the electricity grid expects failure to meet electricity demand. It is an immediate response to prevent damage to the electricity grid and requires cooperation from electricity consumers. Consumers are given incentive payments from power suppliers or disincentives through dynamic pricing programs to cooperate with electricity companies when these DR alerts are announced.

Figure 4 indicates a situation where DR could be useful. Power companies will forecast that electricity consumption will exceed electricity supply capacity one day before and send DR alerts to electricity consumers. Figure 5 indicates how a successful DR might alter the electricity demand curve.

Figure 5 An ideal DR outcome

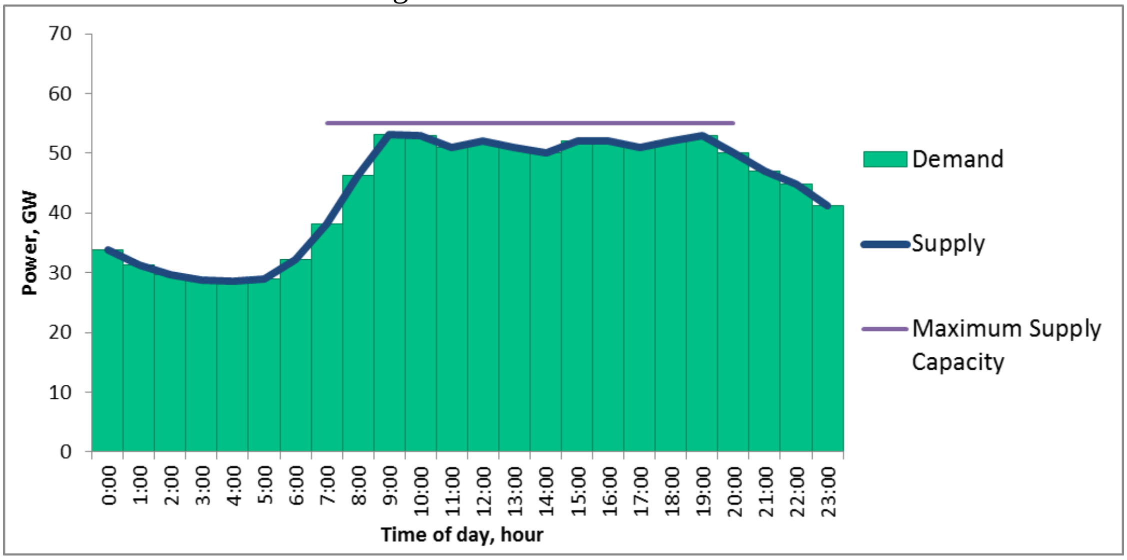


Chart created by author based on [4, 10]

2.7.1 Overview of DR programs

DR programs are classified into incentive based programs and price based programs. In incentive based programs, electricity customers will generally receive payments or credits in other forms as a reward for their cooperation. Price based programs include a variety of dynamic pricing systems that influence electricity consumers to modify their normal electricity consumption patterns during peak demand hours. Time of use rate, critical peak pricing and real time pricing are three distinguished programs in this category.

Time of use (TOU) rate is one of the classical methods of changing electricity prices [10, 11]. There are annually predetermined pricing blocks for on-peak and off-peak hours charging electricity consumed at different prices. The pricing block in peak periods are set higher than off-peak hours to encourage electricity consumers to shift their consumption to off-peak hours.

Critical peak pricing (CPP) rates is another pricing system that builds on the time-of-use pricing system. Power companies will use CPP rates on a limited number of days or hours each year by usually notifying consumers a day ahead. CPP rates generally impose even higher tariffs than TOU pricing on those selected pricing periods [10, 11].

Real time pricing programs use advanced information and communication technologies to adjust electricity prices dynamically based on real time oscillations of wholesale market prices. Customers are required to install smart meters to receive dynamically changing pricing information. [10] Power companies generally provide options that vary from technology intensive real time pricing systems to conventional time-of-use programs, and consumers are free to choose what fits their living styles.

2.7.2 Shared benefits among power companies and consumers

Power companies would suffer profit loss if electricity consumers simply decide to reduce electricity consumption overall. However, electricity companies are likely to support DR to overcome peak demand, as it may reduce maintenance cost of existing power supply capacities. As mentioned earlier, since excessive levels of peak demand (those that exceed total supply level) occur rarely throughout the year, power companies carry redundant capacity that only operate for a short period in any given year. If DR could substitute the redundant power supply capacities, then the profitability of power companies could be increased greatly [10].

Participants in DR programs could also benefit from future savings in their energy bill. If DR becomes a wide spread phenomenon and reduces the redundant capacity that power companies need in order to meet the peak demand, then operating costs for power companies would decline. This may result in lower electricity prices overall [3].

2.7.3 Inconveniences/Costs from DR

DR imposes inconveniences on electricity consumers since electricity users are required to shift their daily routine activities. Businesses may have to reschedule their operations, which could result in losses. For an entire DR system to function, there are initial investments that incur additional costs such as installation of smart meters or energy management systems as well as planning effective responses in times of DR.

From the utility side, there are initial costs of establishing metering and communication infrastructure in the technological aspect. As part of the running costs, the design of billing systems as well as educational systems for participating electricity consumers are also identified as being crucial costs [10].

Chapter 3 PROBLEM STATEMENT

3.1. Sustainability and the Electric Grid

Electricity in a broad sense involves a wide range of issues from the environment, society, and to the economy. In the quest for sustaining the electricity system, we need to focus on developing a system that can continue to provide reliable electricity services today without compromising the needs of the future. From a broader prospective, I feel the need to clarify where this research is positioned in the global shift towards sustainability. The next section briefly discusses existing problems surrounding the electricity grid in a broader sense in terms of sustainability and then, the discussion will return to the main focus of this research.

3.1.1. Comprehensive overview of existing problems

The Fukushima accident in March, 2011, revealed to the world how dependence on nuclear power stations could not only be unsustainable but life threatening. Unless some unsolved issues such as nuclear waste management or disaster compensation programs with the affected areas are resolved, we may need to reconsider the supply of electricity.

However, when we consider the economic benefits of providing secure and equally low priced electricity supply, as well as employment that the nuclear industry has brought, we cannot completely reject the conventional electricity system's power supply. Businesses are also better off with cheaper and more stable electricity services provided. Increasing energy costs accompanied with intense global competition could drive companies to accelerate their shift overseas that could dampen the local and national economy.

If we simply replace the loss of supply capacity with thermal power stations, this will not only increase dependence on depletable fossil fuels, but carbon emission levels are also expected to increase. The volatility involved with natural resource prices has potential to threaten stable procurement and affordable energy prices for consumers. Dependence on foreign fossil fuels also increases the outflow of national wealth. Trillions of yen are expected as additional expenses for securing fossil fuels, which could be spent on securing jobs for the unemployed instead [12]. As these issues identify, there are many problems observed at various levels from local to global and in different time scales.

3.1.2. A paradigm shift to a 'soft energy path'

When we consider a sustainable energy system, Lovins suggested the necessity of a complete paradigm shift on the electricity system. He defines the conventional electric grid as taking a 'hard energy path' criticizing its characteristics of 1) highly centralized supply system, 2) generation far from points of use, and 3) preference on nuclear power. TEPCO covers a vast area of the Kanto plane by controlling every step from electricity generation, to distribution, characterizing a highly centralized supply system. The company's possession of nuclear power plants located outside of their service areas complete the features of a 'hard energy path'. On the other hand, Lovins states that a 'soft energy path' characterized by 1) decentralized supply systems, 2) public participation, and 3) preferences to renewable energy, is what our society should seek [13]. A decentralized supply system is composed of many smaller scaled electricity generation facilities run by diverse power suppliers that are located closer to the points of consumption. Public participation in energy usage is critical to improve energy efficiency as well as reducing total energy consumption [14]. For example, citizens actively involved in purchasing solar panels for their home's usage brings energy production closer to people's everyday lives. This is also explained by the NIMBY to IMBY (not in my backyard to in my backyard) movement, which depicts a paradigm shift for electricity users to achieve sustainable energy consumption [15].

With these sustainability principles at hand, at the technological level, a new emerging movement can be observed with recent projects around the world with smart grids. A smart grid uses the intelligence of information communication technology to manage electricity production, storage, and consumption for an entire community. In such systems, the necessity of having excessive supply capacity only to meet peak demand for a large area diminishes. This new system, with greater diffusion of energy storage and consumer participation can integrate a higher ratio of renewable energy to the grid than the conventional system.

DR is one of the principal consumer participation features in a smart grid. DR is applicable to the current centralized grid, but its importance is expected to increase as our society shifts towards decentralization with preference to renewable energy, and small scale electricity grids that characterize a sustainable energy system.

3.2. Need for Estimating DR Potential

As the importance of DR increases for maintaining the reliability of current electricity services in Japan, understanding the feasibility and potential of DR as a grid healing tool becomes an interesting topic. Modeling and simulation of potential electricity demand reduction based on historical electricity consumption data is one method to understand the effectiveness of DR. Power companies require estimates of predicted DR from a collection of consumers (e.g. factories, shopping centers, cluster of shops, cluster of residences etc.) in order to effectively exercise DR. [16]

One of the reasons why power companies are willing to upgrade conventional mechanical meters with smart meters in Japan is for this purpose. While mechanical meters are simply designed to measure the cumulative amount of electricity consumption occurring since its installation, smart meters are capable of measuring real time consumption levels and report data in short time intervals (e.g. 30 minute consumption values) that enable power companies to monitor compositions of electricity demand at given hours. Power companies use this data to understand real time electricity consumption from each electricity consumer for better use of DR programs. [17]

Electric power companies would consider DR successful if electricity supply shortages are covered with the least effort from consumers. Excessive DRs reduce potential earnings for power companies and also result in excessive behavioral modification from each household. In such cases, the overall welfare for the society in terms of economics is reduced. Under-estimation is also problematic since insufficient DR would result in failure of the electrical grid. Once a power company understands how much electricity reduction it can expect from a cluster of consumers, the company can plan and execute DR accordingly.

3.3. Scope of Research

For the purpose of this study urban condominium type residential households are considered as the focus target for assessing DR potential. The residential sector is one of the greatest contributors of energy consumption increase marking a 30% increase in energy consumption over the last 20 years [18]. In terms of electricity consumption, the residential sector is responsible for 27% of total annual electricity demand [18]. Because of the need to address increases in energy consumption, various industries are targeting energy saving in households as a new business field [19].

Condominium type households are currently more popular than detached dwellings in the Tokyo metropolitan area. Between 2005 and 2011, 38% more condominium housing units were newly constructed than detached households in the same region. [20] The higher preference towards condominium type dwellings by Tokyo citizens increases the significance of focusing on this segment.

3.4. Past Research on DR Potential

Historical studies on DR to the residential sector go back to the late 1970s. The term load shifting was then used to study the potential of energy users shifting electricity consumption to off peak hours (i.e. times of day when electricity is demanded less) using the time of use (TOU) pricing methods. Time of use programs have been a classical approach by power companies to shift demand loading in order to reduce the stress imposed on the electrical grid during peak hours and increase efficiency of power stations. One of the earliest studies conducted by Aigner and Lillard, in southern California found TOU to be effective in shifting the consumption behavior of participants [21]. Caves et al. studied the effect of TOU in service areas of Pacific Gas and Energy on residents that volunteered to take part in TOU programs and found that the TOU programs caused a shift of approximately 5% of electricity consumption [22].

Much later in Japan, Matsukawa et al. designed a TOU experiment in Fukuoka, Japan where participants received incentive payments for reducing the peak usage share of their annual electricity consumption compared to the previous year. Households that received incentives showed a slight shift in consumption compared to those that did not receive incentives, but the authors concluded that the effect was negligible [23].

In recent years around the world, the focus is shifting towards real time pricing and other incentive programs to reduce peak demand more effectively. Deployment of smart meters that give customers feedback on energy use as well as dynamic price changes enable new programs to be introduced. In Japan, the long lasting dominance of vertically integrated and monopolized electricity markets long prevented the introduction of such equipment, and new pricing mechanisms/incentive programs are yet to begin.

Herter et al. conducted an experiment to test the effect of critical peak pricing of electricity in California. They showed a significant residential customer response of up to

13% reduction for households equipped without direct load control equipment and 25% reduction for households equipped with direct load control equipment for a 5 hour duration. They concluded that critical peak pricing with direct load control equipment has a high potential to relieve stress on the electrical grid [24].

In Japan, InterTech Research Corporation conducted a DR pilot study in the Kanto and Kansai regions of Japan applying various pricing programs and direct control measures to subdivided groups of 900 households. The results were reported to be negligible, calling into question the usefulness of DR for the Japanese residential sector [25].

The study by InterTech Research Corporation lacks discussion on the possible reasons for the negligible effects. The experiment was conducted one time in the summer without prior education to participants or an analysis of household characteristics such as living patterns or family structure. In this research, we argue that electricity consumption depends greatly on each household's capacities of taking action. Capacities can range from individual living patterns to awareness of energy saving strategies. Therefore this research will focus on living patterns as well as family structure to discuss strategic measures for effective DR outcomes.

3.5. Research Objective

The objectives of this research are 1) to understand the potential of DR based on predicted human behavior for urban condominiums in Kashiwa-no-ha of Kashiwa City and 2) to identify critical features that affect DR outcomes. This research aims to give recommendations to policy makers or power companies for designing effective DR programs.

3.6. Specifying the Focus (Direct vs. Indirect Load Control)

In DR, there is a distinction between direct load control and indirect load control.

Direct load control is popular in the United States where grid operators are authorized to remotely control each household's energy usage [11]. However, the diffusion of smart meters for enabling direct load control has raised disputes in the United States where consumers protested against the remote shut-off features that power companies would possess [26]. An indirect load control is where households are given incentives or disincentives to change their energy use during DR, but the households choose their own behavior. This research will be discussed in the context of indirect control which is participatory rather than coercive, giving electricity consumers the right to choose their response.

3.7. Research Questions

Part I: Estimating DR potential

- Can DR bring significant peak reduction?

  1a. What were the conditions in which peak demand occurred in the previous year?

  2a. Which households consume electricity during those hours?

  3a. What are possible options for households?

  4a. What percentage of residents can be expected to take each action?

Part II: Relationships between living pattern, family structure and electricity consumption

- How do living patterns affect potential electricity reduction?

  1b. What are regular representative living patterns?

  2b. What is the distribution of different living patterns?

  3b. What is the relationship of family structure to living patterns?

Part III: Recommendations

- What are possible suggestions generated from the findings? What are the implications from the findings?

The first phase of this research involves calculations and running scenarios to understand findings based on selected behavior by electricity consumers. The second phase investigates the relationship between electricity consumption and living patterns, and how different living patterns are linked to family structures. The final phase provides suggestions and recommendations based on the findings for policy makers or power companies to practice DR with greater efficacy.

DR is likely to follow a developmental process that is impossible to justify by a single experiment at an initial stage. The design of DR programs as well as the availability of continuous feedback and consumer education should greatly affect the outcomes. The calculations of DR potential using historical electricity consumption data will simply serve for setting target goals. [11] The next step explores how household living patterns and family structure are hints to discovering peak cut tactics.

Chapter 4 DATA AND METHODOLOGY

4.1. Data

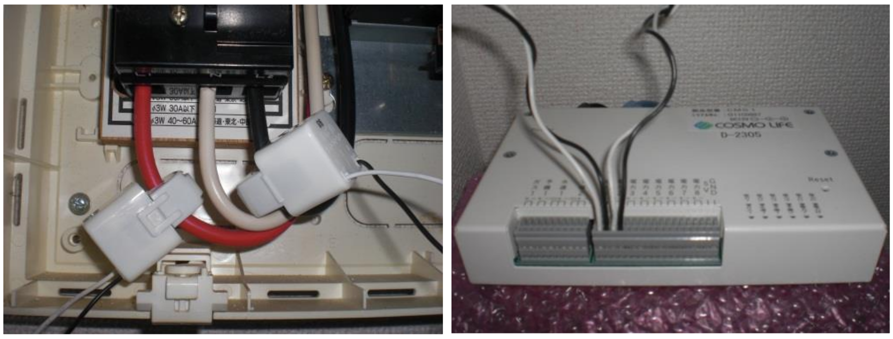
Electricity consumption data is collected from condominium residential buildings located in Kashiwa-no-ha of Kashiwa City. The sample size is 94 households and electricity measurements are collected at 10 minute intervals from October 1st , 2011 to September 31st, 2012. The selected households demonstrated reliable data submission from the electronic electricity meters with more than 95% of data successfully stocked in the data server each month of its duration.

4.1.1. Data collection

In each household of the residential district, an electronic meter that measures consumption of electricity, water and gas by 10 minute intervals is preinstalled. For the purpose of the study, the method for electricity metering is only described. On the distribution board of each residential unit, a current transformer (CT) is attached to the red and black voltage side electric wires. The CT collects all electric current that flows through both wires and measures the entire amount of electricity consumption for a single household in a given time interval.

Figure 6 An image of a typical Japanese distribution board

Figure 7 CT attached to the voltage wires (left) and data collector (right)



This instrument collects and sends electricity reading records via the wireless LAN to the energy data center. The data center processes all data and gives feedback to individual households via a social network system (SNS) and an interphone [27].

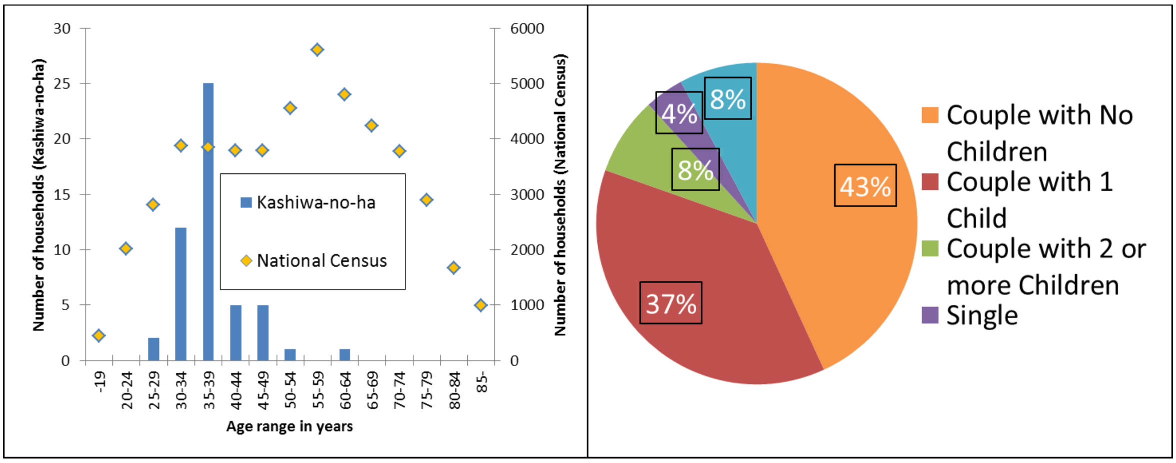
4.1.2. Data characteristics:

Currently more than 200 households continuously submit energy consumption data to the database. However due to instability of data submission observed in some households as well as constant increases in new residents, we have restricted the sample size to 94 households. Once the entire condominium complex is complete, collection of data from 800 households is expected. Thus the current sample size represents approximately 12% of the future total.

Residents interact through an SNS that is built-in to the condominiums before they move in. Active participants were requested to provide information on family size, family composition and household head's age. All information for 51 of the 94 households that we have targeted was successfully collected.

Family attributes show highly skewed distribution towards younger families and smaller family sizes. Approximately 80% of the families were couples having either one or no children. With a large majority of the household head's age in the 30s, the families are considered typically young.

Figure 8 Distribution of household head age (right) and family structure (left) both retrieved from the social network service's database



Source: [28]

4.1.3. Advantages of using this data

Since all data is collected from a single geographical site, there are no climatic factors that differentiate among different households. If data were dispersed throughout the country, energy consumption is likely to change depending on factors such as temperature, irradiation, or weather.

The sample size is also advantageous. Currently 94 households are monitored consistently and continuously producing 10 minute interval energy data. This size is important because, household electricity consumption differs widely among different households and this large collection of data should represent the whole population's distribution well.

Unified building structure is an additional benefit of using this data. The units of this condominium type residential block are all built with unified material and are rated under the CASBEE building rating system with the highest standards [27].

The Hawthorne effect in this study is expected to be insignificant. The Hawthorne effect is a type of bias that often occurs when conducting social experiments to people [29]. The theory states that when people are conscious of monitored for purposes of social experimentation, their behavior is likely to become biased. In the case of our target residential buildings in Kashiwa-no-ha, all energy meters are pre-installed to the each unit before the resident moves in. Therefore, it is likely that the data depicts the natural living patterns of residents.

4.2. Methodology for Estimations

4.2.1. Input data

- Data format: 10 minute interval total household electricity consumption data
- Duration: October, 1st 2011 to September, 31st 2012
- Sample Size: 94 households from Kashiwa-no-ha condominium residences
- Temperature Data: Retrieved from the Japan Meteorological Agency's Abiko station

Sample selection was based on the reliability of each household's electricity meters. While some electricity meters faced unstable wireless internet connection, the selected sample for this research showed excellent data transmission consistency with over 95% of data retained for each month in the 12 month period.

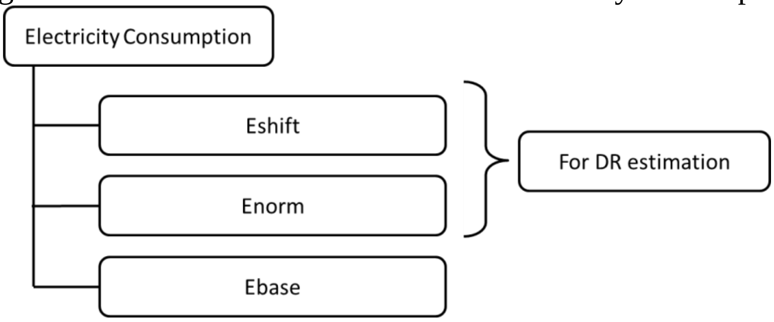
4.2.2. Output features

- Values: E_{norm} and E_{shift} per household (these are described below)
- Time intervals: 1 hour cumulative values
- Dates: 5 highest summer peak demand days for TEPCO's supply area in 2011

TEPCO's summer demand peak is selected as the setting for DR estimation. In the summer, the demand peak is reached in the early afternoon, but demand stays quite high between 10AM and 6PM on a weekday. Therefore, our estimations will focus in this hour range. We estimate DR potential based on the following assumed human behavior model. Occupants are assumed to respond to DR in three possible ways: 1) stay inside the house and reduce electricity consumption, 2) leave the house and switch off all electricity consumption except for base loads such as refrigerators, 3) continue using electricity the same as before.

As an initial step to estimate the amount of reducible electricity, we classify all electricity consumption into 3 categories as indicated in figure 9.

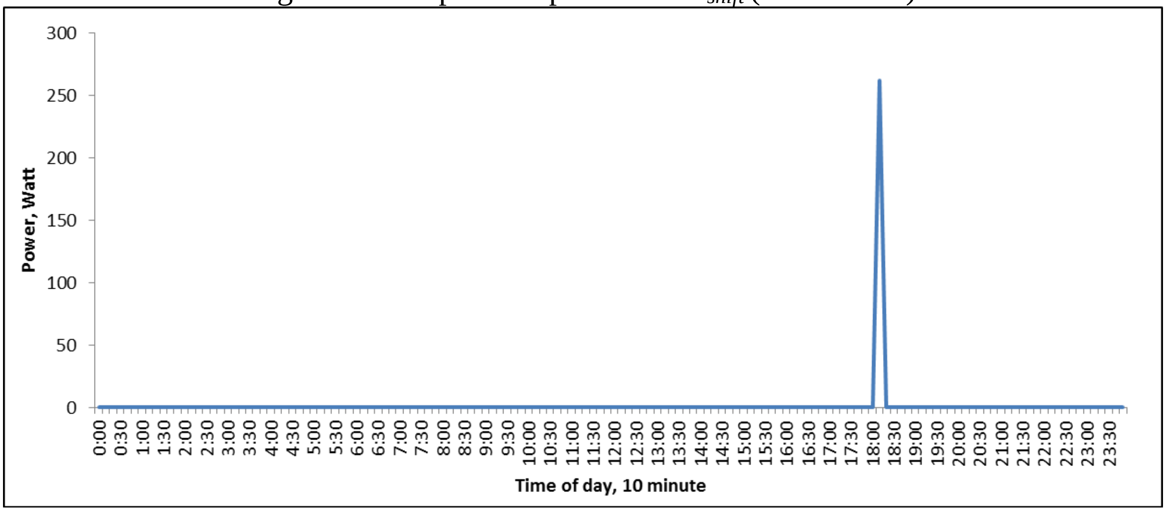
Figure 9 Classification rule of household electricity consumption



4.2.3. Defining E_{shift}, E_{norm}, and E_{base}

E_{shift} is electricity consumption that an individual household is capable of shifting for a given period of time. The assumption here is that this type of consumption is characterized by short intervals of intensive electricity consumption, which results in sharp peaks in the consumption profile. These consumption types are also considered to be mostly unrelated to living patterns, occurring on an essentially random basis. Some examples of E_{shift} type electricity consumption include microwaves, toasters, vacuum cleaners, hair dryers, or washing machines.

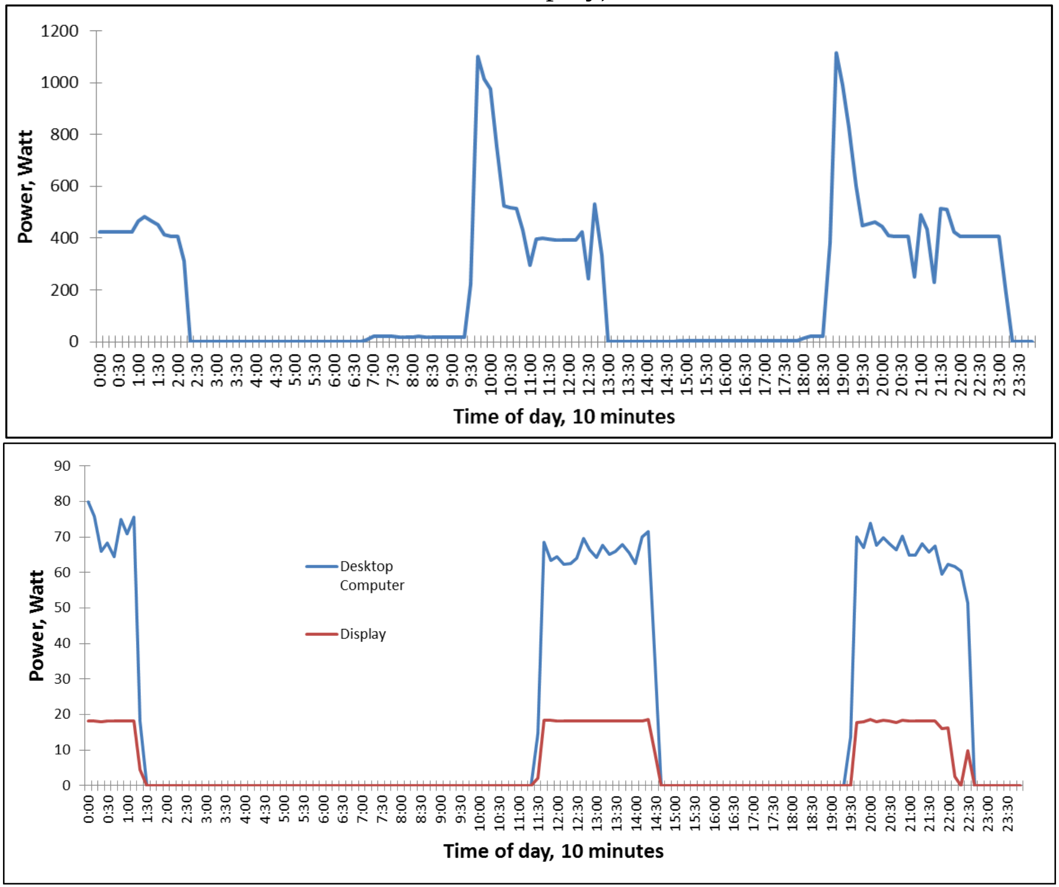
Figure 10 Sample load profile for E_{shift} (Microwave)



Source: Direct measurements conducted by the author

E_{norm} consists of electricity consumption that an individual household regularly consumes while occupying the house. When household members stay inside the house, there are certain appliances that consume electricity at all times regardless of what they are doing. For example, some residents may always have lighting, air conditioning, television sets, personal computers, and/or the humidifier on during the entire time that they are in the house. Such consumption is categorized as E_{norm} consumption, and I assume that this consumption cannot be shifted to other hours unless all family members in a household leave the house.

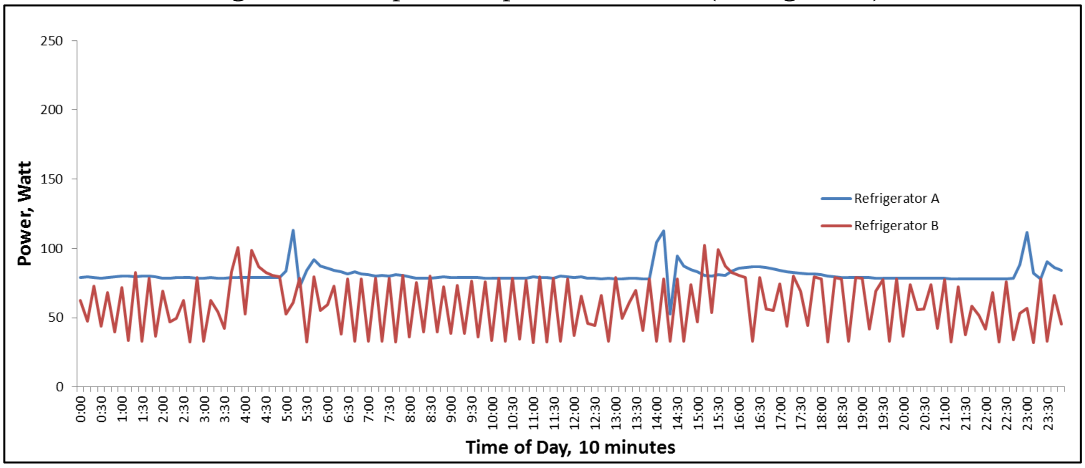
Figure 11 Sample load profile for E_{norm} (Above: air conditioner, Below: Desktop Computer and Display)



Source: Direct measurements conducted by the author

We also define E_{base}, although this value is only used indirectly for estimating DR potential. E_{base} includes electronic appliances that operate 24 hours per day regardless of household occupancy. A typical 24 hour consumer of electricity is a refrigerator.

Figure 12 Sample load profile for E_{base} (Refrigerator)



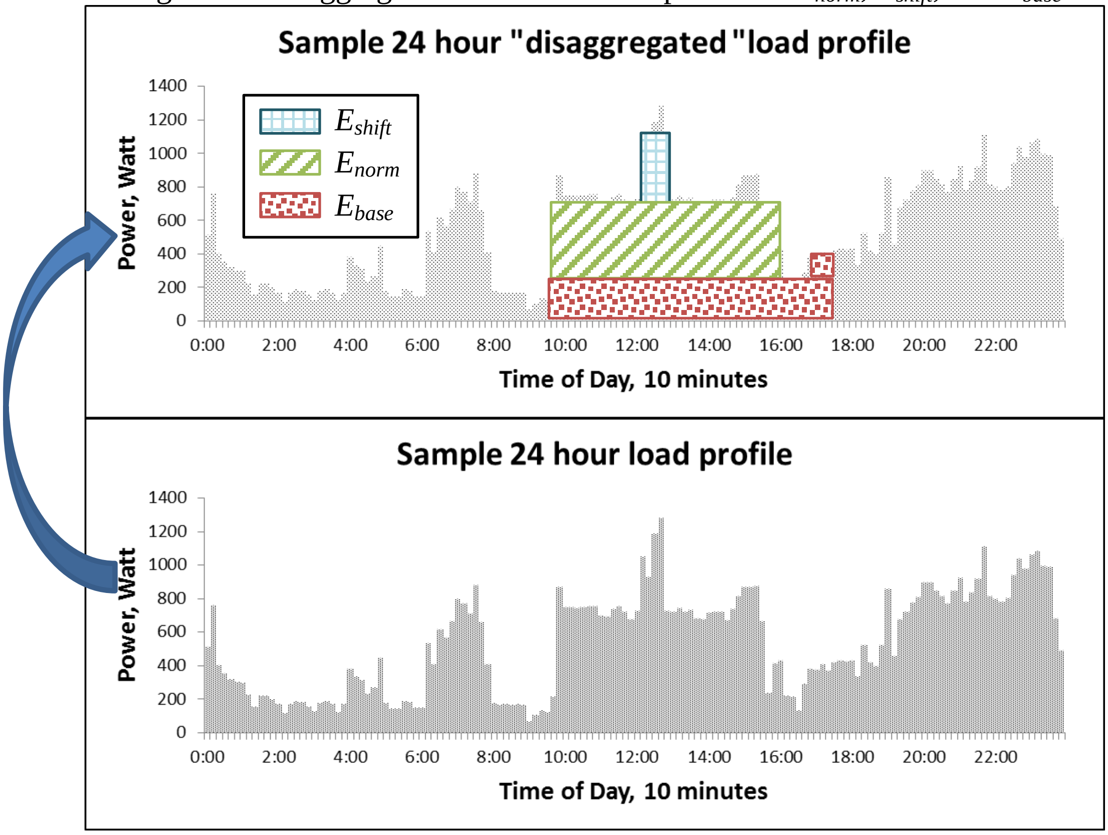
Source: Direct measurements conducted by the author

The two sample profiles of different models of refrigerators depict differing load profiles. While "Refrigerator A" shows a smooth pattern, 'Refrigerator B' depicts a rougher pattern with frequent but small fluctuations. More recent models that are eco-friendly may show this rough pattern, which generally results in a much smaller total energy consumption. Another example of an appliance that consumes electricity 24 hours per day is the heated toilet seat that is popular in Japanese households. Simple standby electricity consumption by unused but plugged in appliances are also classified in this group.

4.2.4. Disaggregating E_{norm} and E_{shift} from total consumption

This subsection will explain the methodology I have developed for estimating the values of each consumption type for individual households. Figure 12 indicates how total electricity consumption of a household is disaggregated into E_{norm}, E_{shift}, and E_{base}.

Figure 13 Disaggregation of total consumption into E_{norm}, E_{shift}, and E_{base}



Source: Data collected from a selected sample household in Kashiwa-no-ha

E_{norm} and E_{shift} are the amounts of electricity consumption above E_{base} consumption. We assume that they only occur when residents occupy the house, although this assumption means that we ignore situations such as when the residents run washing machines while they are outside of the house. As figure 12 shows, when residents are in the house, electricity consumption tends to reach a plateau indicated on the top of the diagonally striped boxes. This plateau is the level of electricity consumption from E_{norm}. For this sample household, the plateau is at around the 800 watt level. All consumption readings exceeding this level are considered as a part of E_{shift}. We will name this 800 watt level as e_{basic}. e_{basic} is the level of power consumption that distinguishes E_{norm} from E_{shift}. All E_{norm} and E_{shift} are energy consumption calculated each hour between 10AM and 6 PM.

4.2.5. Estimating E_{norm} and E_{shift}

There are two steps to estimate E_{norm}, and E_{shift} for each household. The first step is to detect occupancy for the hours between 10AM and 6PM. To do this, we use a process that refines the raw data into simplified forms that eliminate minor fluctuations but keep major fluctuations. By processing the raw data in this way, only abrupt changes that indicate the beginning or the end of occupant activity remain. The second step is to determine e_{basic}, which is the level of power consumption that distinguishes E_{norm} from E_{shift}. e_{basic} is the power consumption level for a minimum livable indoor ambience for the occupant. In this research, all consumption above the e_{basic} is considered to be shift-able. Consumption at or below the level of e_{basic} is considered to be non-shift-able: this electricity will be consumed unless occupants leave the house and switch off all appliances. The assumption is that electricity users will not give up the livable ambience provided by e_{basic} when they are staying indoors.

4.2.6. Occupancy detection (the first step)

For a selected 24 hour period of meter readings over 60 minute intervals for a particular household, the following equation is used to assign a unitless value to each meter reading.

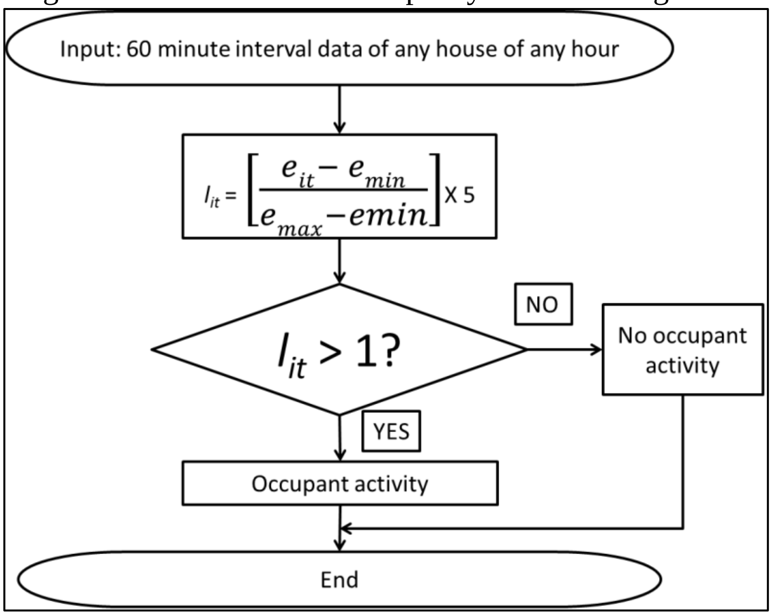
$$l_{it} = \left[\frac{e_{it} - e_{min}}{e_{max} - e_{min}}\right] \mathrm{x}\, 5 \tag{1}$$

lit is the amount of electricity used by household *i* at time *t* normalized to a value usually between 0 to 5. Whenever e_{it} is greater than the estimated e_{max}, lit could have a greater value than 5. ei_t is the actual measurements of power consumption by household *i* at time *t*. e_{min} is the estimated lowest power consumption value for the target date's consumption while e_{max} is the estimated maximum value of power estimated for the target date.

Each e_{min} and e_{max} for a given household is determined as follows. e_{max} is estimated by initially identifying the daily maximum power consumption values of 60 minute interval data over the previous 7 days I then take the average value over all the 7 values to determine e_{max}. e_{min} is estimated by taking the minimum of 60 minute interval daily minimum data from the past 7 days. We have used the previous 7 days of data in order to eliminate the following types of biases. If the occupant happened to be home all day and used the air conditioner for 24 hours, the minimum value of the actual day will not reflect minimum levels of consumption when the occupant leaves the house and switches off all appliances. In a similar manner, if the occupant is absent from the house for holidays, the maximum value of the actual analysis day will be useless. Observing the past 7 days helps to exclude those bias factors. (Refer to the Appendix A)

The following equation is then applied to all of the processed data as a rule to determine occupant activity. This rule of distinguishing occupant activity enables further understanding of living patterns. (Refer to Appendix B)

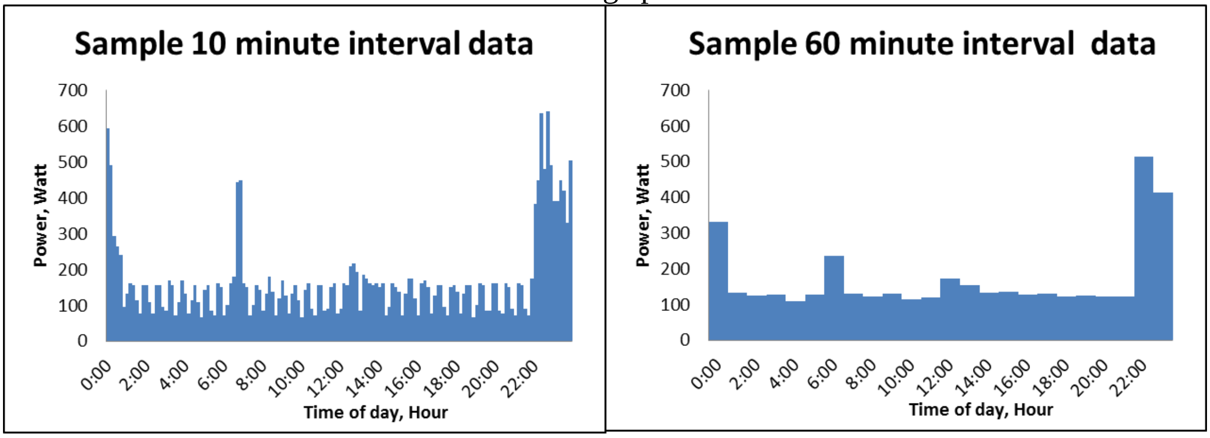
Figure 14 Flow chart for Occupancy Detection Algorithm



4.2.7. Solving for e_{basic} (the second step)

I use the original 10 minute interval data to calculate E_{norm} and E_{shift}, because 10 minute interval data depicts sharp rises and declines of electricity consumption changes better than 60 minute interval data as indicated in figure 15.

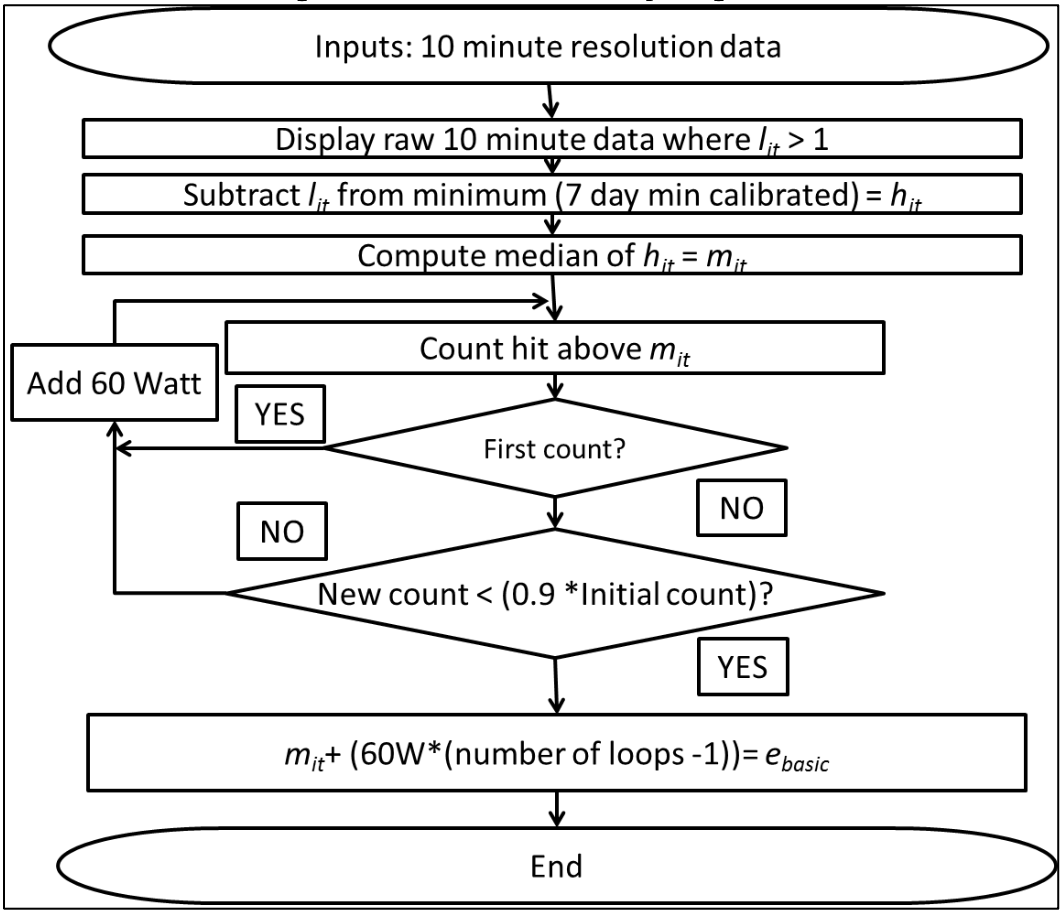
Figure 15 A comparison between 10 minute interval average power data and 60 minute interval average power data



The method is as follows. For the hours in which there was occupant activity, (i.e. l_{it} > 1) subtract a e_{min} from all 10 minute interval data between 10AM and 6 PM to obtain h_{it}. The value of h_{it} is understood to be the electricity consumption from activities that occur as a result of the household member being in the house. Occasionally, h_{it} will be a negative value. This can occur because even though a 60 minute interval data may depict household occupancy, one of the six 10 minute interval data may not. The base load refrigerator profile is likely to cause minor fluctuations where values fall below e_{min}, and I have ignored such values.

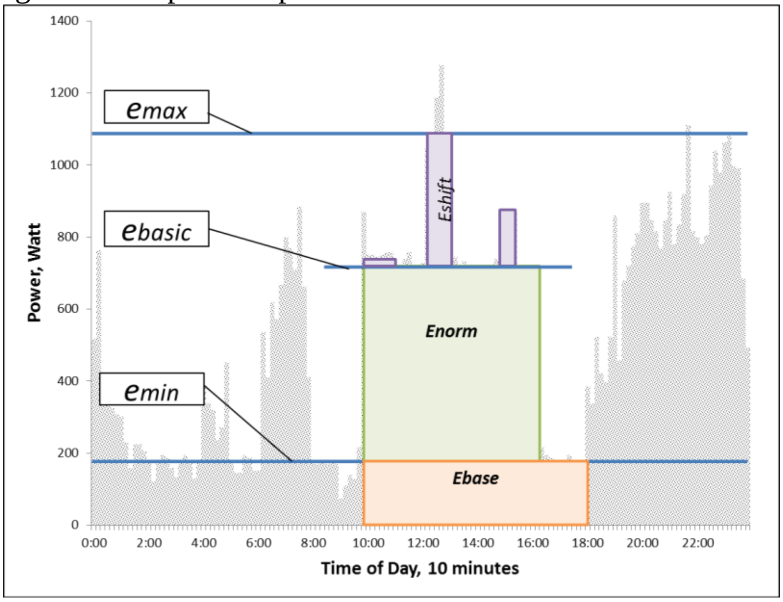
I use an iterative method to establish the value of e_{basic}. First, I set the initial value of e_{basic} to be the median value of h_{it} for a given household on the analyzed date. I then count the number of h_{it} values that are above e_{basic}. If more than 90 percent of the h_{it} values are above e_{basic}, I increase e_{basic} by 60 watts and then repeat the count. (Refer to Appendix C)

Figure 16 Flow chart for computing e_{basic}



E_{norm} and E_{shift} are calculated using e_{basic} as follows. Any values of h_{it} that exceed e_{basic} are considered non-shift-able consumption patterns included in (E_{shift}). The remainder of h_{it} is considered shift-able (E_{norm}). For clarification, figure 17 provides a graphical representation of each variable identified in this methodology section.

Figure 17 Graphical representation of the 6 variables identified



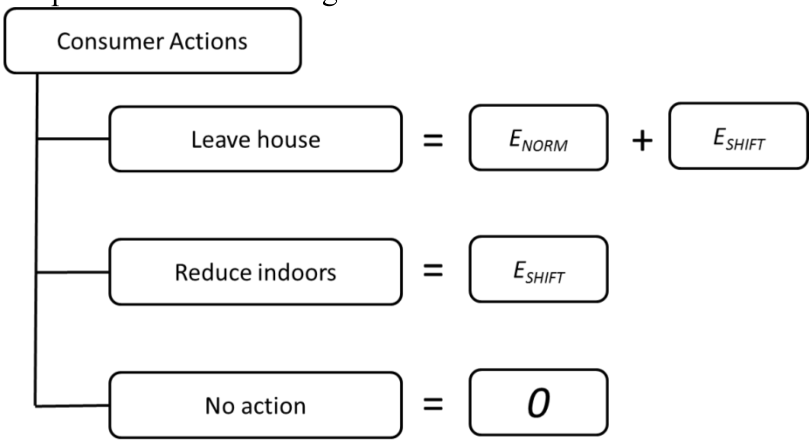
Source: Source: Data collected from a selected sample household in Kashiwa-no-ha

4.2.8. Solving for E_{NORM} and E_{SHIFT}

So far we have explained the steps to solve E_{norm} and E_{shift} for individual households. However, we seek to understand the total potential of electricity reduction from the entire residential building. We aggregate every E_{norm} and E_{shift} from all households to get E_{NORM} and E_{SHIFT} that represent the total building's values. E_{NORM} is the total amount of non-shift-able electricity consumption over a predetermined period of time (one hour) calculated for all households assessed. E_{SHIFT} is the total amount of shift-able electricity consumption calculated for all households assessed. All letters are capitalized to distinguish between the values estimated for individual households and aggregated values estimated for the entire residential building.

Once E_{NORM} and E_{SHIFT} are calculated, the potential electricity consumption reduction based on each of the consumer actions, 1 Leave house, 2 Reduce electricity consumption while staying indoors, and 3 No action can be calculated. The total amount of electricity that would be reduced by leaving the house over the specified period of time (one hour) is the sum of E_{NORM} and E_{SHIFT}. The total amount of electricity consumption that can be reduced while staying indoors is E_{SHIFT}. Figure 18 illustrates the rules of calculation.

Figure 18 Equations for estimating 'Leave house' and 'Reduce indoors'



4.2.9. Aligning the Units

So far, all estimations for E_{norm}, and E_{shift}, were in units of energy consumption (Wh) per each hour. In numerical terms, this watt-hour per hour is equivalent to the average power consumption (watts) for the same time interval. DR is about power savings rather than energy saving. Power is the instantaneous level of electricity consumption for a particular moment. Analyzing the potential DR of an instantaneous power demand for a household is impossible with the current resources I have. However, we can attain a good estimate of the power level for a particular time interval by aggregating a large collection of datasets. Instantaneous demand could oscillate dynamically, but by aggregating hundreds of electricity consumption data, the fluctuations occurring at different moments in a particular hour interval cancel out to form a rather smooth estimate. In this research, I estimate E_{NORM}, and E_{SHIFT} in units of Wh per hour, but I treat the potential DR outcomes in terms of watts (W) reduced.

4.3. Scenario setting

I have evaluated three scenarios depending on the participation ratios for each action. Complete participation in "leave house" depicts the unrealistic situation where all DR participants decide to leave their houses. This value gives the maximum reduction amount possible from the DR program considered here. The other two scenarios are more realistic situations that include smaller ratios of participants who elect to leave their houses and a significant percentage of non-participating residents who take no action.

Table 1 Scenario setting

Scenarios	**Leave house**	**Reduce indoors**	**No action**
Complete Participation	100 %	0%	0%
Medium Participation	40%	30%	30%
Minimum Participation	20%	40%	40%

If the residents that decide to leave the house end up consuming the same amount of electricity elsewhere, the contributions to DR from those individuals will be nullified. Therefore, it is important to design the DR program so that household members gather at public spaces that share an air conditioned environment. The overall energy consumption is expected to decline as people gather and share energy use.

4.3.1. Complete Participation

In this situation, those residents consuming electricity during the critical peak demand hours will all decide to leave their houses for a certain period of time. This is a highly unlikely scenario since it is difficult to imagine all residents abandoning an entire residential building for energy saving purposes. However, values calculated for this scenario could give an understanding on the maximum potential for the DR program considered here to contribute to reduction of peak electricity demand.

$$\text{Complete Participation} = E_{NORM} + E_{SHIFT} \tag{2}$$

4.3.2. Medium Participation

In this case, 40% of the occupants in home are expected to participate by leaving their house during the peak demand hours, while 30% would participate in their houses by shifting some activities earlier or later than the peak demand hours. Therefore, it is assumed that in total, 70% of all residents in their homes would contribute to DR, generating numbers that are more conceivable in a real situation. Through experience and improved design of DR programs, we expect to achieve results similar to this scenario.

$$\text{Medium Participation} = (40\%*(E_{NORM} + E_{SHIFT}) + (30\%*\ E_{SHIFT}) \qquad (3)$$

4.3.3. Minimum Participation

In this scenario, 20% of households inside the house will leave the house and 40% would decide to shift consumption to other non-peak hours. Therefore, the total participation rate is 60%, leading to a smaller impact than the other two scenarios. At the initial stage of DR, we expect outcomes to be similar to this scenario.

$$\text{Minimum Participation} = (20\%*(E_{NORM} + E_{SHIFT}) + (40\%*\ E_{SHIFT}) \qquad (4)$$

4.3.4. Significance of each scenario

These scenarios serve as benchmarks on the responsiveness of the residents to DR. The effect of DR should grow as more citizens are exposed to the program and gain experience. At the initial stage, the DR effect may fall way below expectations, but as citizens become aware of available actions, the results from the Medium Participation and even Full Participation scenarios may become achievable.

Chapter 5 RESULTS

5.1. E_{NORM} and E_{SHIFT} Calculated

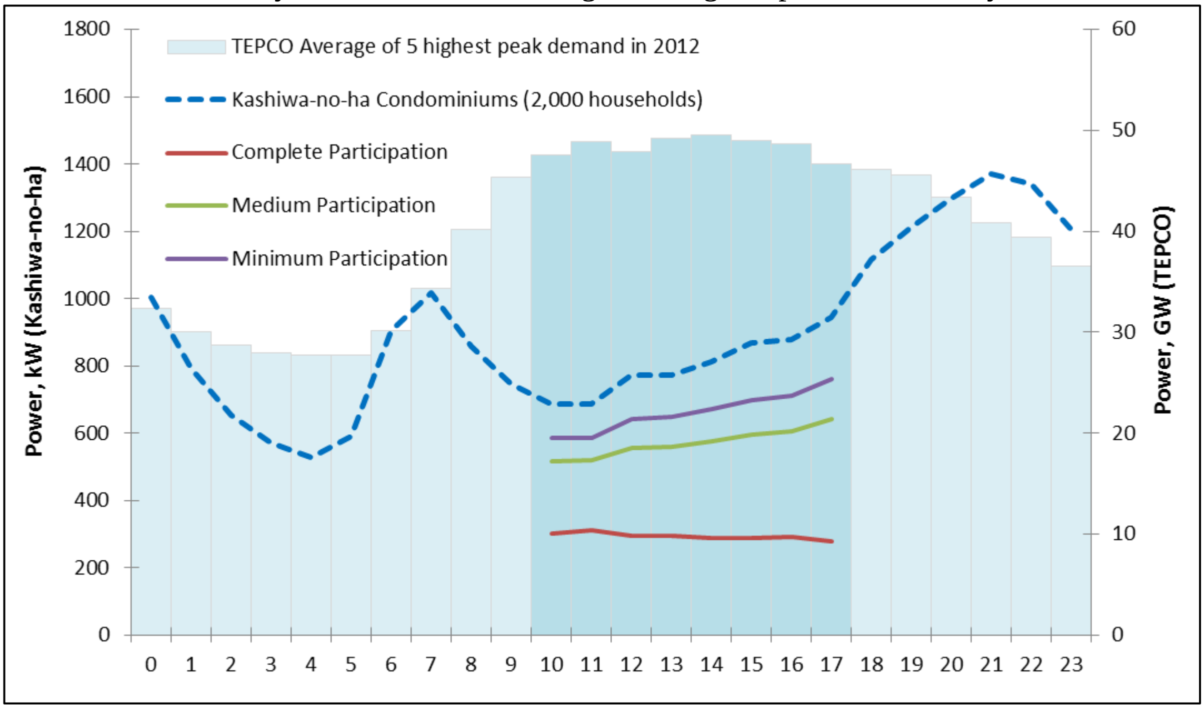
E_{NORM} (non-shiftable electricity consumption) and E_{SHIFT} (shiftable electricity consumption) for the entire condominium buildings of Kashiwa-no-ha is estimated. Every value of $E_{norm\ it}$ and $E_{shift\ it}$ for each household in the 94 samples was calculated and then averaged to compute per house values. Assuming that the 94 households represent Kashiwa-no-ha, per house values were multiplied by 2000 to attain the residential building's value.

Table 2 E_{NORM} and E_{SHIFT} estimates on the average of 5 highest peak demand days

	Weekday Summer 2012								
Hour	10	11	12	13	14	15	16	17	Average
E_{NORM} (kWh per hour)	325	311	391	408	435	445	463	545	415
E_{SHIFT} (kWh per hour)	60	64	86	72	89	135	124	120	94

E_{NORM} and E_{SHIFT} were calculated for the five highest peak electricity demand days of the TEPCO service area. Those values were averaged to obtain the values on the table. E_{NORM} and E_{SHIFT} are used to compute scenario results.

Figure 19 Graphical representations of Kashiwa-no-ha residential demand (94 sample total) and DR outcome by scenarios on the average of 5 highest peak demand days for TEPCO



Source: [4]

Table 3 Residential DR outcome by scenarios on the average of 5 highest peak demand days

Weekday Summer 2012									
Hour	10	11	12	13	14	15	16	17	Average
Complete Participation (kW)	386	376	477	480	524	580	587	664	509
(% reduction)	(-56.2%)	(-54.6%)	(-61.7%)	(-62.0%)	(-64.5%)	(-66.8%)	(-66.9%)	(-70.5%)	(-62.9%)
Medium Particpation (kW)	172	169	216	214	236	272	272	302	232
(% reduction)	(-25.1%)	(-24.6%)	(-28.0%)	(-27.6%)	(-29.1%)	(-31.4%)	(-31.0%)	(-32.0%)	(-28.6%)
Minimum Participation (kW)	101	101	130	125	141	170	167	181	139
(% reduction)	(-14.7%)	(-14.7%)	(-16.8%)	(-16.1%)	(-17.3%)	(-19.6%)	(-19.0%)	(-19.2%)	(-17.2%)

Under the Medium Participation scenario, an average of 232 kilowatts of power consumption can be reduced from the condominium residential building, which corresponds to a 32% electricity reduction of the data population. Greater or lesser electricity cuts will result if participation levels change. The minimum participation would generate a 17.2% reduction on average and the complete participation would result in a 62.9% average reduction.

5.2. Significance of ~28.6% Peak Reduction from the Residential Sector

When we consider a society, households differ greatly with respect to building characteristic, family income, geographical location, or energy type dependence. However, if we assume that the entire residential sector under TEPCO's service area (30% of the total demand in the service area) reduces 28.6% of electricity demand during peak demand, the effect on the TEPCO peak electricity demand would be a reduction of 8.58%. [30] Peak demand of TEPCO in the summer of 2012 was 50.17GW and 8.58% of this value is approximately 4.3 GW.

5.3. Significance of 4.3 GW

We can compare the 4.3 GW of reduction from DR to the electricity supply capacity of nuclear reactors in Japan. Prior to the Fukushima Daiichi nuclear disaster in March, 2011, there were 17 nuclear reactors operating for TEPCO. The average capacity of each of the 17 nuclear reactors in TEPCO service area was 1.01GW [31]. Therefore, the total electricity consumption reduced from the residential sector is approximately equivalent to 4 and one quarter of nuclear reactors.

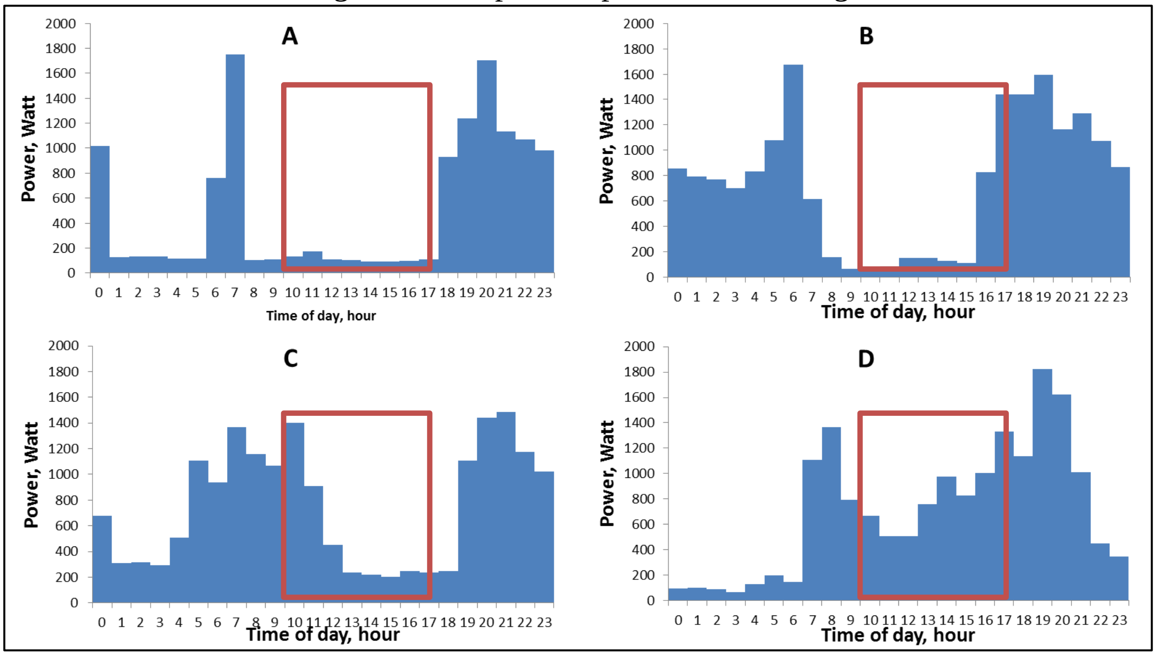
5.4. Observing Different Living Patterns

In the following section, we analyze the relationship between living patterns and family structure with electricity consumption in order to clarify the attributes that could contribute to effective DR participation. We believe that by understanding the two attributes we can better plan tactics to reach more effective DR outcomes. The aim of this section is to deepen data analysis to deliver effective recommendations to DR operators.

5.4.1. Analyzing representative living patterns of electricity consumption

I conducted an extensive study over different living patterns from several hundred households, which resulted in a rough classification of living patterns indicated in figure 20.

Figure 20 Sample of representative Living Patterns



The red brackets indicate the hours between 10:00 AM and 6:00 PM, corresponding to the hours in which people usually work. We classify the household living patterns based on the different forms of electricity consumption profiles within each bracket.

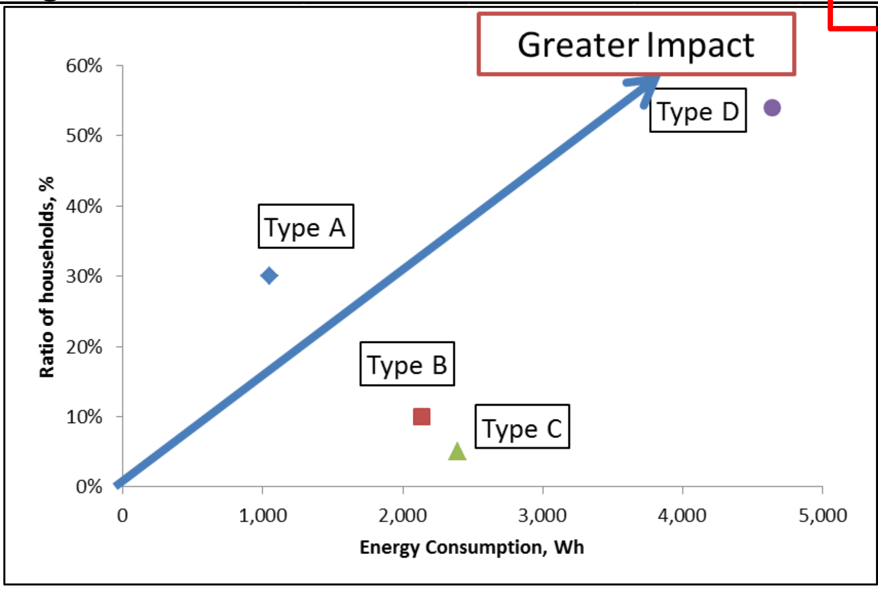
Table 4 Summary of representative living patterns

Pattern	*Characteristics*	*Example situations*
A	Absent during the daytime	All family members work or go to school during the day.
B	Present in the morning and absent from the afternoon	Mother and young child leave for shopping in the afternoon.
C	Absent in the morning but returns home early afternoon	Young child returns home in the early afternoon from school on weekdays
D	Present all day	An elderly family member stays in the house all day. Air conditioning is left on all day for a pet that is taken care of in the house.

On the same days that were used for estimating DR potential in the previous analysis, we investigated the distribution of different living patterns.

Figure 21 Tabular and graphical view on ratios of living patterns by day

Date (temperature)	*A*	*B*	*C*	*D*
2012/8/30 (28.9)	31%	12%	6%	51%
2012/7/27 (28.4)	30%	5%	5%	60%
2012/8/23 (28.7)	27%	15%	3%	55%
2012/8/24 (28.7)	29%	9%	6%	56%
2012/8/02 (28.4)	33%	12%	5%	50%
Average	30%	10%	5%	54%
Average demand (Wh)	1048	2136	2392	4639



Approximately 30% of the households are representative of type A while 54% are representative of type D. Type B and type C were less often observed. The final row of the table indicates the average electricity consumption per pattern between 10AM and 6PM. Type D patterns consume far more electricity than other patterns.

Residential buildings with high percentage of type D households would have large potentials for DR because more households simply consume greater electricity during the day. In the same manner, motivating the households showing type D patterns to participate in DR would result in greater outcomes.

5.4.2. Regularity of each pattern

On any particular weekday, we can find the distribution of different living patterns for that day. However, observing the regularity of each pattern by individual households is necessary to understand the relationship between family structure and living pattern. Using the five highest peak demand days from the earlier analysis, the regularity of each living pattern for every household was observed. A particular living pattern is assumed to be regular for a household if it occurs at least 4 days out of 5. (Appendix D)

Table 5 Living Pattern regularity of 94 households

Pattern	*Type A*	*Type B*	*Type C*	*Type D*	*Other*
Number of Households	18	0	0	43	33
Ratio	19%	0%	0%	46%	35%

No families showed regularity for type B or type C patterns. 19% of the sample households remained absent during the day for 4 days or more indicating type A patterns, and 46% of the sample households consumed electricity throughout the day for 4 days or more, indicating type D patterns. The remaining 35% of the sample households demonstrated no adherence to any of the living patterns.

5.4.3. Redefining electricity consumption patterns

Since none of the households showed regularity for type B and type C patterns, we merged those patterns with the “Other” group into a group ‘Partial Absence’. We redefine households showing regular type A patterns as ‘Total Absence’, and households with regular type D patterns as ‘Non-absence’.

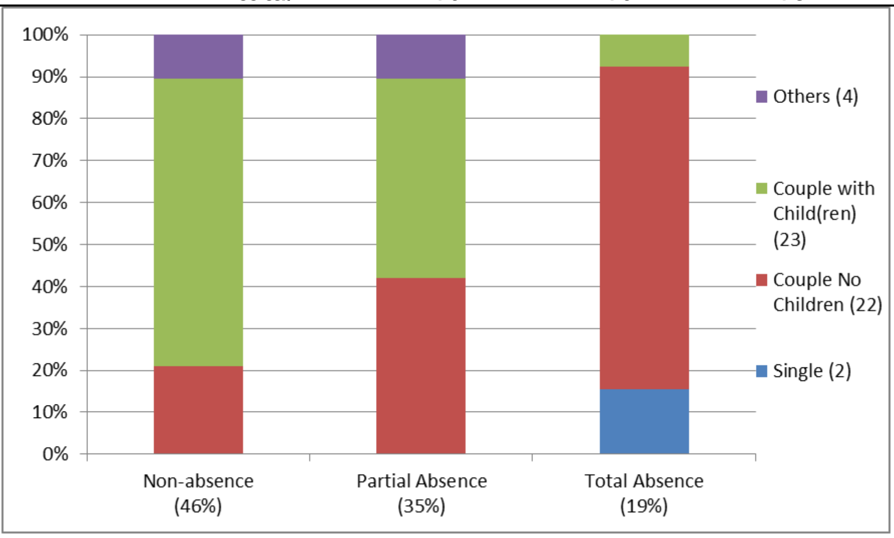
5.5. Family Structure and Electricity Consumption Patterns

The next step seeks to understand the relationships between regular consumption patterns and family structure. Out of the 94 households used for analyzing electricity consumption data, we successfully collected family structure information on 51 households. Family structures of the remaining 43 households are unknown, but an analysis of family type dependency on each of the three groups was conducted otherwise.

Families are categorized into 4 groups which are 1) single, 2) couple living with no children, 3) couple living with children, and 4) others. The category 'others' is comprised of families where the household owner lives with their parents.

Figure 22 Tabular and graphical representation of the relationship between family structure and regular living patterns

Family Structure	*Non-absence (46%)*	*Partial Absence (35%)*	*Total Absence (19%)*	*Total*
Single (2)	0	0	2	2
Couple No Children (22)	4	8	10	22
Couple with Child(ren) (23)	13	9	1	23
Others (4)	2	2	0	4
total	19	19	13	51



Results show that nearly 70% of the households showing 'Non-absence' are families with one or more children. Although a minority, those families under the category 'other' that have elderly family members also tend to stay inside the house on a regular basis. Families under 'Total Absence' are dominated by smaller family sizes such as single households or couples living with no children. In ‘Partial Absence’ group, different family structures are mixed.

5.6. Summary of Results

At the first stage of analysis, DR estimation found an approximate 28.6% reduction of electricity use for summer TEPCO peaks. This estimate involved a close look into individual household’s electricity consumption profiles for the tested dates. The significance of this figure was later calculated to give a rough estimate of 4.3 GW potential reductions from the entire residential sector under TEPCO service areas. This value was comparable to the power capacity of 4 and one quarter of an average nuclear reactor of TEPCO property.

The second stage involved a deeper observation into different living patterns that each household follows. Each household was roughly categorized into 4 representative patterns based on the time of electricity use. A comparison of the number of households each category indicated that 55% of the households consumed electricity on a consistent and constant basis throughout the day. This group labeled “type D” households was the greatest consumer of electricity during the day, and it was concluded that demand participation from this group would have the greatest impact on reducing electricity consumption during the peak.

Although it was understood that type D pattern was the most common and most electricity consuming, we also wanted to understand the regularity of each electricity consumption pattern. For each household, the tendency to stay with each pattern was studied. Results showed that 46% of the households were consistently labeled as type D pattern. Type B and type C patterns had no regularity. Type A patterns appeared 19% of the time and the remaining 35% of the households involved a variety of different patterns (type A through type D patterns) with no specific regularity. This part of the analysis concludes by forming 3 new groups that are labeled as, ‘Total Absence’, ‘Non-absence’, and Partial Absence.

The final step observed the relationship between family structures and the 3 new groups of living patterns. The ‘Non-absence’ group was composed nearly 70% by couples living with children. ‘Total Absence’ was composed more than 90% by either single households or couples with no children.

Chapter 6 DISCUSSION (RECOMMENDATIONS)

6.1. Strategy Planning for Effective DR Outcomes

Table 6, is a list of recommendations for each corresponding group. There are two types of recommendations with different ends. The first is advising ways to encourage household members to leave the house for a temporary period and switch off all electricity consumption except for the base load consumption. The other is to consider how to reduce electricity consumption while staying inside the house either by shifting the activity or eliminating wasteful electricity consumption.

Families with 'Non-absence' consumption patterns were mostly families with young children. We can assume that while one parent takes care of the children, the other is out for work. Reasonable suggestions would include ways to motivate parents and children to gather outside of the house, (e.g. at shopping malls or other public facilities), and create social interactions with other families of a similar kind. Ice cream shops or cafes could distribute discount coupons to residents that are in the house to bring their children outside. Amusement facilities may also become another important location to attract these young families with children. Although, small in percentage, families with elderly family members were also labeled with 'Non-absence' consumption patterns. If movie theatres could provide senior discount tickets or if public facilities could organize social gatherings targeting these people, then a significant reduction in electricity consumption could be expected.

We also expect that many residents would prefer to spend their time in the house rather than leaving the house on a hot summer day. If a household still chooses to participate in DR, then it is important that these households understand effective practices that reduce electricity consumption indoors. One of the fundamental ways to participate is by shifting consumption activity to different hours. For example, vacuuming the floor, or washing the clothes are shift-able to other hours of the day depending on the individual's priorities. The initial DR estimate conducted in this research is based on people's choice to shift consumption. However, people could achieve greater electricity consumption reduction by cutting the use of large electricity consuming appliances in the house. Some of the largest electricity consuming appliances in an average household are identified as the air conditioner, refrigerator, lighting, and television [30]. One simple strategy is to understand which of those 4 categories of consumption are consuming the most electricity. If households that share some basic features (e.g. geographical location or size) could compare their levels of consumption on each of the 4 categories of consumption, then each household should be able to identify their target of focus. A feedback system that incorporates appliance-specific breakdowns is proven effective [31].

The second largest group 'Partial Absence' was families that showed no attachment to a particular living pattern. These households are still flexible in terms of mobility since members of the household tend to stay and leave the house from time to time. Occupants of these types of households could most effectively reduce electricity consumption during peak hours by modifying their schedule either by leaving the house early or returning to the house late.

Families showing 'Total Absence' living patterns represented nearly19% and the main family structures were single or couples with no children. Since these people are almost never in the house during the day, the only contribution is by reducing the level of electricity running 24 hours as much as possible. Measures to do that include setting the refrigerator at low consumption mode, or identifying appliances that consume standby electricity and unplugging them.

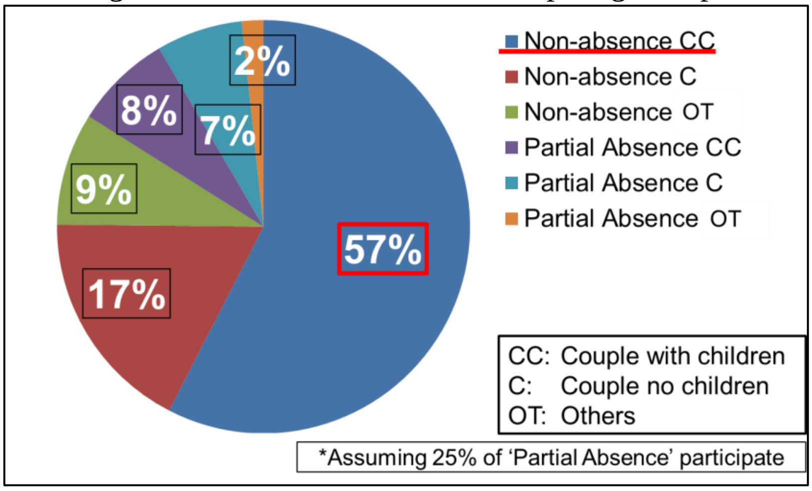
Table 6 List of recommended actions by living pattern

	Issues	Solutions	
	Families Structure	i) Leave House	ii) Reduce Indoors
Non-absence	Dominant Family Structures – Couple with Children (70%) – Couple no Children (20%) – Others (10%)	Visit public spaces –Residential lounges –Library/community centers Entertain/Enjoy –Ice cream shops, cafes etc.. –Movie theatres –Amusement Park	Refrain additional electricity use. Check air conditioner, lighting, and, television. Switch off or curtail intensity on the lowest priority use.
Partial Absence	Dominant Family Structures – Couple with Children (50%) – Couple no Children (40%) – Others (10%)	Extend stay at destination 1.Return home later 2.Leave home earlier	
Total Absence	Dominant Family Structures – Couple no Children (75%) – Singles (10%) – Couple with Children (5%)	N/A	Cut standby electricity 1.Unplug unused appliances before leaving the house 2.Operate refrigerator at “low”

6.1.1 Maximum potential effect per recommendation

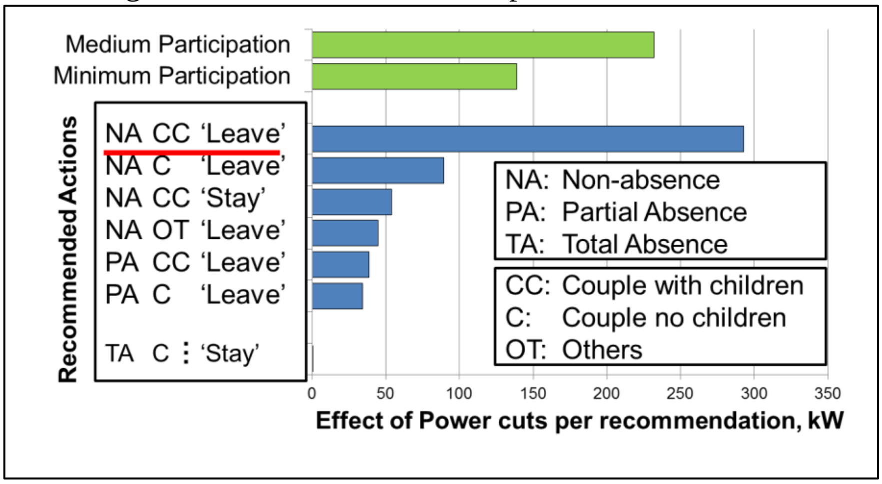
For any given residential area, the maximum effect of all recommended actions would highly depend on the size of each classified group. Here, I evaluate the effect of recommended actions listed on table 6 within the residential area of the sample data. Since 'Non-absence' and 'Partial Absence' are the only groups that would mainly participate in DR, I first calculate the ratio of each family subgroup within the 2 living pattern groups. All 'Non-absence' groups are considered to be potential participants but only a quarter (25%) of 'Partial Absence' will be considered potential participants due to its random nature.

Figure 23 Distribution of DR Participating Groups



'Non-absence'/'Couple with children' represents 57% of all potential participants being the largest group. Thus, the greatest DR outcome is expected with this group's full participation. I then compare the maximum DR effect per recommendation in the figure below, by multiplying the ratio of each group by the maximum impact from the action 'Leave', which is leaving the house and switching off all appliances except for the base load consumption, and for 'Stay', which is reducing electricity consumption while staying indoors.

Figure 24 Maximum DR Effect per Recommendation



As expected, the impact from 'Non-absence'/'Couple with children' is far greater than all other recommendations. Comparisons with the two scenarios suggest that 'Medium Participation' is equivalent to approximately 80% of 'Non-absence' / 'Couple with children' leaving the house.

6.2. Motivational Factors

The essence of this research is providing suggestions of actions that people could take in order to more effectively address peak cuts from urban condominiums. The motivational factor that encourages people to take those suggested actions is another area that would complement the work of this research. The following section mentions key aspects that need consideration to motivate people and deliver the desired DR results.

6.2.1. Rule making

In order to encourage households to take action, a system that could generate monetary or non-monetary rewards to participants is important. The level of rewards one could earn should depend on the level of participation. Special consideration shall be given to those households that decide to leave the house during the peak demand since this not only requires large efforts but also results in the greatest reduction. For participants reducing inside the house, rewards shall depend on the level of consumption achieved.

6.2.2. Financial sources

I suggest that either TEPCO or DR management companies (i.e. demand aggregators) should be the source of financial resources for realizing all the activities. As mentioned earlier, TEPCO has the incentive to cut peak demand. Because TEPCO is forced to possess power supply that only operates during the very few hours when the peak demands occur, reduction of extra supply capacity could significantly cut running costs.

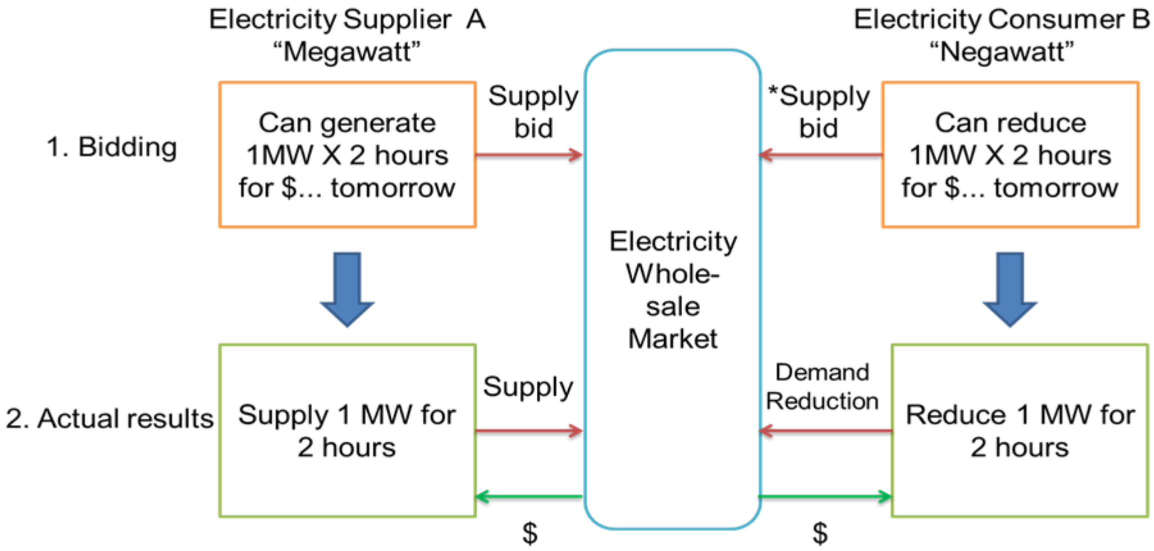
6.2.3. Negawatt

Negawatt refers to the amount of electricity consumption that is reduced. Under a negawatt system, the amount of electricity consumption reduced is considered equivalent to the amount of electricity generated. The negawatt thinking is one popular system of generating economic incentives to those participants in DR [32].

In deregulated electricity markets such as those observed in parts of the United States, or Europe, there are multiple businesses involved in the electricity infrastructure at different levels. Nordpool is a Scandinavian wholesale electricity market initiated by Norway in 1993.This country launched its deregulation program by introducing a wholesale market that promoted competition among electricity suppliers. Electricity suppliers and distributors exchange bids based on market prices. By 2000, Sweden, Finland, and Denmark had joined the system making it the world’s largest wholesale electricity market with 300TWH of electricity exchanged [33].

The principal objective of the wholesale electricity market is to have balanced bids of electricity supply and demand. In such systems, supply biddings and demand reduction biddings are treated equally. Whenever expected electricity demand exceeds expected supply, demand reduction biddings are valued more than ever. Demand reduction biddings can bid with the same economic value of those bids by electricity suppliers. Figure 24, indicates how electricity supply biddings and demand reduction biddings are considered equally.

Figure 25 Diagram of supply biddings of Negawatt and Megawatt in a electricity wholesale market



Source: [33, 34]

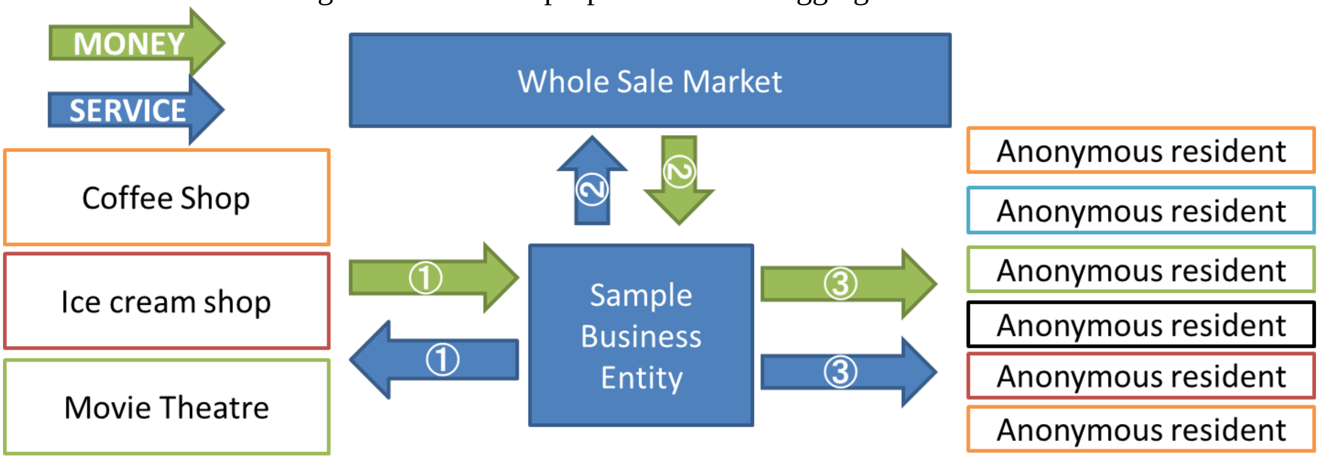
The economic incentives for reducing electricity consumption during the peak are generated through this system. Those participants in DR programs can earn money through cooperation. Applying this model to provide services that will incorporate consumer participation is discussed in the next section.

6.2.4. DR aggregator business; Negawatt application on business

We identified recommendations to generate better demand reduction outcomes for the condominium type residential sectors studied. In a negawatt system, individual households are incapable of bidding in a wholesale electricity market due to its small contribution. Therefore, new businesses that aggregate household electricity demand reduction emerge as one tactic for joining the bidding scheme.

Recommendations we provide involve local businesses such as coffee shops or movie theatres in town. As mentioned earlier, the most effective electricity demand reduction an individual household can execute is leaving the house. To achieve this objective, one method is to lure residents out of the house by providing discount information of the resident’s favorite places to gather.

Figure 26 Business proposal for a DR aggregator



Service flow	*Money flow*
①Access for advertisement rights	①Monthly access fee
②Successful peak cut	②Reward for successful peak reduction
③Coupon distribution to selected customers	③Reward for DR participation

Figure 25 indicates a sample business model emerging as a DR aggregator. DR aggregators are business entities that will aggregate all the DR participation efforts of residences willing to participate in DR programs. Although contributions at individual levels are small, aggregating participatory efforts from hundreds of households result in kilowatts of demand reduction. We develop a model that connects advertisement rights for shops that are willing to attract customers during the daytime. Shops are capable of providing advertisement to the right customers that are in the house during the day. If possible, by linking customer’s historical purchasing data, shops can directly send recommendations to suit each customer’s preferences. Participating households will benefit both from rewards received through participating in DR as well as coupons received from their local shops. The DR aggregator business gains small revenues from DR reward payments from the electricity wholesale market and payments of advertisements rights from supporting local shops. Note, that the DR aggregator protects privacy of individual households by coordinating between residents and shops. Those participating shops will not have direct access to the resident's energy data. One of the limitations is that DR does not occur frequently. Therefore, for such a business entity to survive, another business model that generates returns on a consistent basis is necessary.

6.3. Limitations

6.3.1. Limitations with living patterns

Type D households simply could have been sick and sleeping, or they may keep a pet dog indoors while the human occupant stayed elsewhere. Therefore, there are still uncertainties with the classification of living patterns.

6.3.2. Leaving the house

DR estimates are based on people choosing to either leave the house or stay indoors. The most important rule that requires absolute attention is not consuming greater additional electricity elsewhere. If the residential sector reduces consumption at home but increases consumption in the community, there is no meaning to DR. Therefore, people who decide to leave the house must gather in public areas where an additional individual would not increase the total electricity consumption.

6.3.3. Estimations based on carefully drawn assumptions

In the first step of data analysis, households that decide to leave the house are assumed to switch off all appliances and reduce electricity consumption levels to minimum levels. In the real world, there is always human error involved where some consumers simply forget to switch off appliances. The other estimation that involved shifting electricity consumption of particular appliances to other times is highly theoretical. The assumption is based on the findings observed while measuring electricity consumption patterns of both the entire house and by appliance in the author’s house. These assumptions may differ widely from house to house.

6.3.4. Applicability

The findings from this research are specific to the residential units in Kashiwa-no-ha, Japan. The ratio of families in each family structure as well as different living patterns will vary greatly depending on location. However, the 3 groups based on living patterns (Total Absence, Non-absence, and Partial Absence) and their strong relationship to family structures is likely to be common in other parts of the Kanto region. Therefore, the recommendations summarized on table 6 should have positive effects.

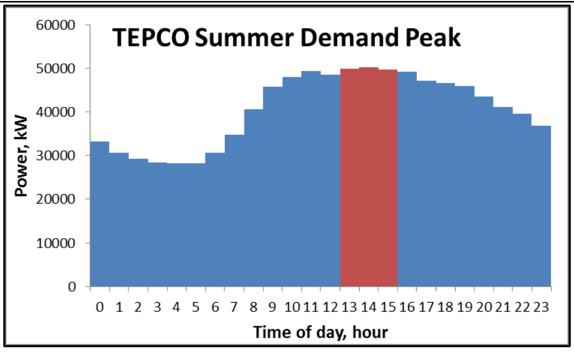
6.4. Future Work

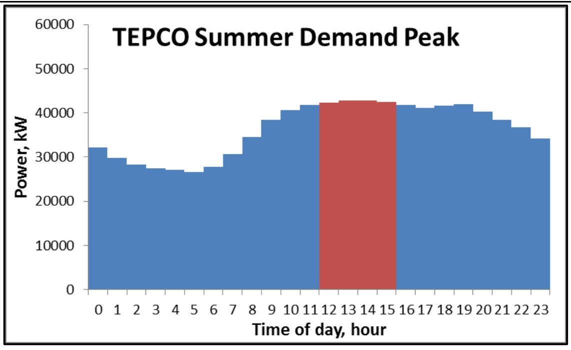
6.4.1. Other peaks

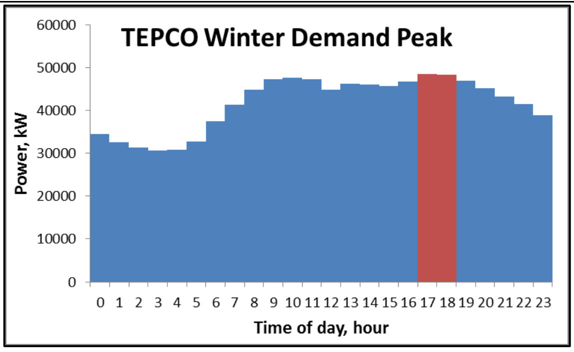
For this research, peak demand for TEPCO service areas in the summer was considered, but there are other situations where peak demand occurs depending on the scale of the grid in consideration. The hours in which DR is necessary would alter depending on the scale of the grid in consideration, type of day, and season. In those three contexts, the following table identifies a general overview of different peaks each categorized in the 3 contexts mentioned above.

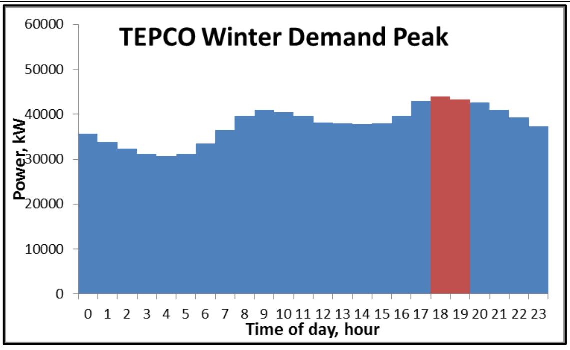
For each category the curves indicate an average value of the 5 highest maximum demand days in 2012. The Maximum Peak is the highest point from the curve and peak hours indicate the hours in which demand was greater than 99% of the its peak. All values under the peak hours are colored in red.

Table 7 Summer and Winter Peaks in TEPCO service areas

<table>
<tr><th>Weekdays</th><th>Weekends</th></tr>
<tr><td>

Maximum Peak: 50.17 GW
Peak Hours: (1 PM~3 PM)</td>
<td>

Maximum Peak: 42.80 GW
Peak Hours: (12 PM~3PM)</td></tr>
<tr><td>

Maximum Peak: 48.56GW
Peak Hours: (5PM~6PM)</td>
<td>

Maximum Peak: 43.86 GW
Peak Hours: (6 PM ~ 7 PM)</td></tr>
</table>

Source: Charts recreated by author [4]

Findings from comparing distinct TEPCO demand peaks

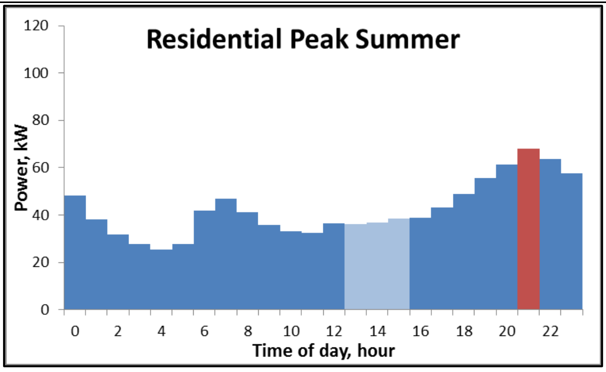
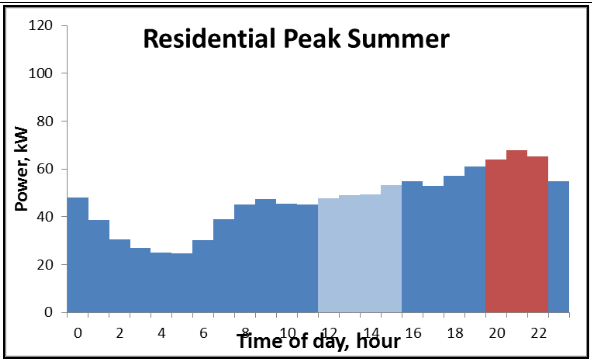
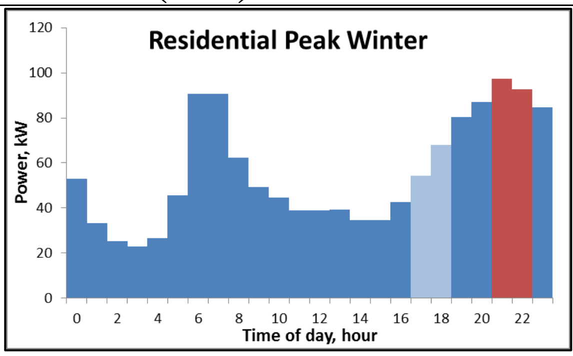
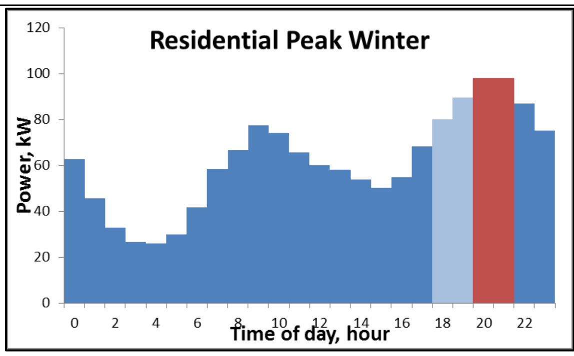
- Depending on season and day type, magnitude as well as the hours of demand peak differ
- Depending on the peak to address, strategies to effectively reduce electricity consumption differ

6.4.2. Peak from the residential sector alone

Currently there are governmental discussions on deregulating electricity markets and constructing a “smart grid” shifting towards smaller scale electricity grids with more local energy production and local energy consumption. Under such transitions, observing the local grid’s peak shall become necessary, and in such cases, the peak may occur at different hours. Similar to the previous table, the target area’s peak was analyzed with the understanding that at a smaller scale grid with different energy users, peaks from the residential sectors may reflect the local grid's peak.

Similarly to the previous table, based on the four seasonal and day type characteristics, different electricity demand peaks are displayed. Each figure shows a computed value of aggregate electricity consumption from the 94 households used for this analysis. The 5 highest peak demand days of 2012 under each category were selected and average values were computed accordingly per each hour. The peak hour bars colored in red indicate those hours in which 95% of the highest peak demand was observed.

Table 8 Residential peak demand by season and type of day

Weekdays	Weekends
 Maximum Peak: 68.1 KW Peak Hours: (9 PM)	 Maximum Peak: 67.7 KW Peak Hours: (8 PM~10PM)
 Maximum Peak: 97.3 KW Peak Hours: (9PM~10PM)	 Maximum Peak: 98.0 KW Peak Hours: (8 PM ~ 9 PM)

Source: Aggregate demand of 94 target households in Kashiwa-no-ha

Some of the findings from observing the variety of the residential sector's electricity load are listed below.

- Peak for the residential sector is observed between 8PM and 10PM regardless of season.

- Weekdays in the winter experience a sharp increase between 6AM and 7AM where in some days with high demand the morning peak exceeds night peak.
- Night hours shall have the greatest potential in addressing DR for the entire society

6.4.3. Strategy planning for residential DR on other peaks

As indicated on the charts above, electricity demand peaks occur at different times of the day. Thus a direct application of summer day-time measures will not function to address the peak on the other occasions and a different approach to address peak demand is necessary.

Demand peaks in the winter for TEPCO as well as year-round peaks for the residential sector itself are observed in later hours of the day compared to the summer time. TEPCO's winter demand reaches the peak between 5PM and 6PM, and the residential sector experiences demand peaks between 8PM and 9PM in both winter and summer. Late hour peaks are expected to differ from day time peaks in the following context

- Shops and stores are usually closed later in at night
- Leaving the house after dark may involve danger in some areas

Therefore, there are limitations on the options available for DR programs in the residential sector. However, since demand is high, there is a high demand reduction potential. Table 4.8 gives a summary.

Table 9 Comparison of the strengths and weaknesses between summer peak strategies and winter peak strategies

	Day-time (Summer Peaks)	*Late Afternoon ~ Night (Winter Peaks)*
Options	Abundant	Limited
Potential	Modest	High

Another issue needing attention is conflicts with other demand peaks. While TEPCO announces a need for demand reduction on a cold winter day at 5 PM, some households may respond by shifting some of their consumption to later hours. However, because peak electricity demand for the residential sector is usually around 9PM, this may increase electricity consumption at that hour. Thus a simple shift of electricity consumption to other hours may augment electricity demand at a different scale.

This area will become a new field to investigate as part of future studies. With a more comprehensive understanding of different approaches to achieve greater DR results, electricity grid operators will gain greater confidence.

Chapter 7 Conclusions

Conclusions

As total supply capacity of electricity significantly decreased in TEPCO's service areas as a result of the nuclear plant accident, meeting peak electricity demand has become an increasingly difficult task. This research has explored the potential to resolve this threat by using DR focusing on condominium residential sectors. Special recommendations are provided to help practitioners of DR to obtain as much electricity demand reduction as possible.

This research began by estimating potential electricity demand reductions during peak demand using 10 minute resolution electricity consumption data obtained from 94 condominium units in Kashiwa, Japan. Utilizing data from the 5 highest peak demand weekdays in summer 2012 under TEPCO's service areas, potential demand reduction was calculated based 3 possible human responses. 1, leave house, 2, shift consumption to off peak hours, 3, no action. 3 scenarios were set with different ratios of electricity consumers deciding to take each of the three options.

Under Medium Participation (scenario: 40% leave house, 30% shift, 30% no action), we estimated that the condominium residential building with 2,000 units would reduce approximately 232 kW equivalent to a 28.6% reduction on average of electricity consumption between 10PM and 18PM. Although, a rough estimate, this 28.6% percentage reduction was multiplied by the proportion of the residential sector's electricity consumption ratio (30%) under TEPCO's service during the peak demand hours (10AM to 18PM). 4.3 GW was the potential power savings calculated and this is equivalent to the power capacity of 4 and one quarter of average size nuclear reactors of TEPCO's property.

These results led us to investigate household attributes that affect levels of demand reduction. Living patterns were observed by categorizing each household into 4 representative living patterns. Type D, which is a pattern that shows continuous consumption between 10AM to 6PM, represented 55% of the sample observed. We also became interested in observing how each household is dependent on any of the living patterns. We identified that 19% of the sample households showed a tendency to be absent during the day, 46% were generally present throughout the day and 35% had no particular dependence on any of the patterns. In this 35% of the sample households, it seems that family members have random and potentially flexible scheduling.

The next step investigated the links between living patterns and family structure. We identified that 68% of households that stayed in the house all day were couples with children. Another trend showed that families with elderly members were also likely to show type D patterns on a continuous basis. Therefore providing services that encourage these electricity consumers to participate in DR programs and leave the house will have the greatest impact on reducing peak demand.

In the discussion section we provide a list of recommended actions to corresponding living patterns and family types which we identified.

Table.6 List of recommended actions by living pattern

	Issues	Solutions	
	Families Structure	i) Leave House	ii) Reduce Indoors
Non-absence	Dominant Family Structures - Couple with Children (70%) - Couple no Children (20%) - Others (10%)	Visit public spaces -Residential lounges -Library/community centers Entertain/Enjoy -Ice cream shops, cafes etc.. -Movie theatres -Amusement Park	Refrain additional electricity use. Check air conditioner, lighting, and, television. Switch off or curtail intensity on the lowest priority use.
Partial Absence	Dominant Family Structures - Couple with Children (50%) - Couple no Children (40%) - Others (10%)	Extend stay at destination 1.Return home later 2.Leave home earlier	
Total Absence	Dominant Family Structures - Couple no Children (75%) - Singles (10%) - Couple with Children (5%)	N/A	Cut standby electricity 1.Unplug unused appliances before leaving the house 2.Operate refrigerator at "low"

We also need to take into account about the possible changes in demographic structure in the future. The current situation in Kashiwa-no-ha with younger households is likely to change over time. When the demographic trends change, so shall the strategies to be implemented. In order to sustain a DR program, the program must also have features to adapt to such social changes.

Motivational factors are also important areas that need consideration. We state that rulemaking as well as ensuring financial sources are critical for running DR. Collaborations among different players in the electricity market and consumers shall also play an important role in this field's innovation. We additionally provide information on electricity wholesale markets that would emerge as a result of deregulation in the Japanese electricity market. A business proposal for DR aggregation in the residential sector is also inserted to demonstrate how the business sector shall take part in this new system. Since we truly believe that DR outcomes are better achieved through educating and improving the design of DR programs, we hope that our findings from this research help the Japanese electricity market launch an effective and smart DR program for the residential sector.

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APPENDIX A

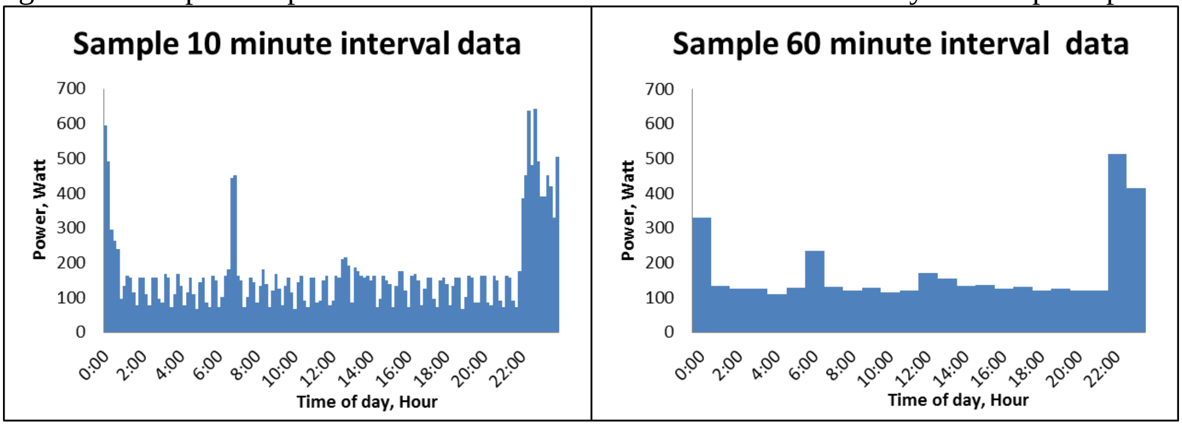
Determining e_{max} and e_{min}

e_{max} is the maximum amount of electricity consumption expected over any 60 minute interval from a particular household *i* on time *t*. Similarly, e_{min} is the minimum amount of electricity consumption expected over any 60 minute interval from a particular household *i* on time *t.* Estimates of both values are necessary to run the occupant detection algorithm.

Using 60 minute interval energy data

In this analysis, 60 minute interval data is used instead of the original 10 minute interval data, where the 60 minute interval data is calculated by simply averaging the six 10 minute interval data points within each 60 minute. With 10 minute interval data, distinguishing the base load consumption is difficult. Figure A1 compares 10 minute interval and 60 minute resolution on the same data set taken on August 2, 2012.

Figure A1 Sample comparison of a 10 minute and a 60 minute electricity consumption profile

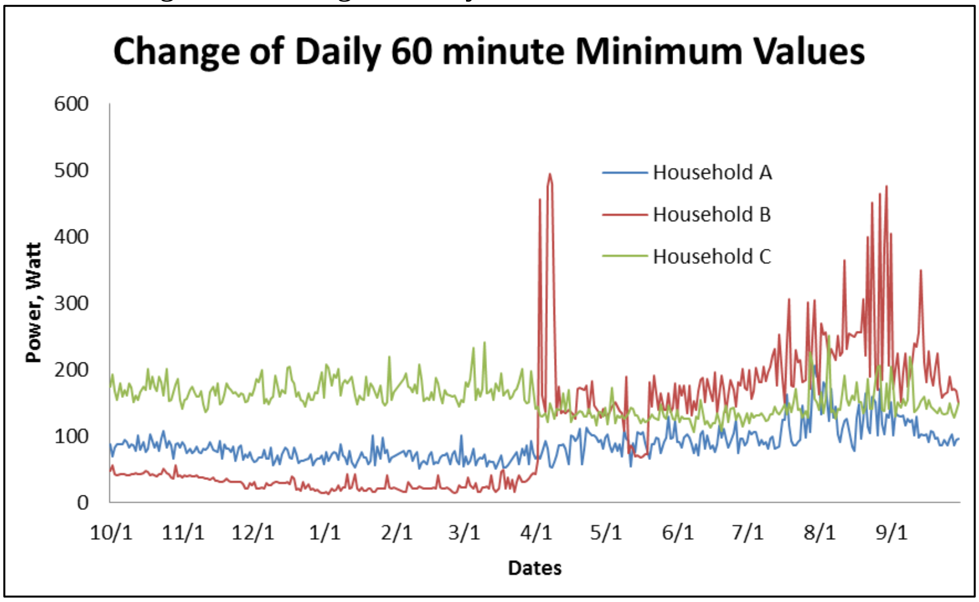


Base load consumption is mainly composed of the refrigerator. A unique characteristic of many refrigerators is that they operate on a cycle of intensive and non-intensive periods of electricity consumption throughout the day. Such movements cause minor but frequent fluctuations of electricity consumption patterns to appear in a 10 minute interval data. By observing the same data set in 60 minute intervals, the small fluctuations cancel out and become smooth facilitating the estimates for the base load consumption. In the 60 minute interval data set, base load is approximately at the 100 watt level, but with the 10 minute interval data, the base load is barely distinguishable. Utilizing 60 minute interval data will also smooth the maximum electricity consumption values that differ day by day.

Determining the number of previous days to observe

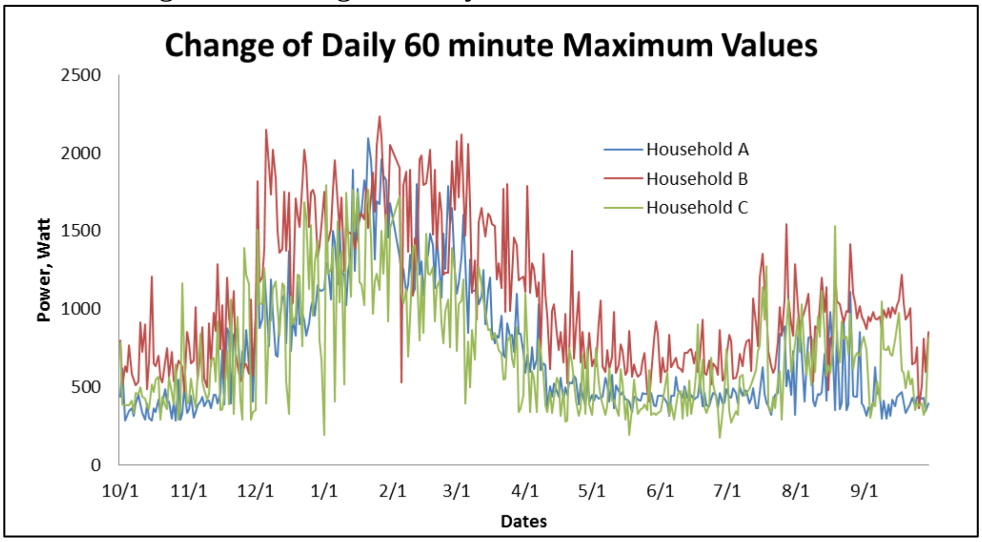
To calculate e_{min} *and* e_{max}, we must observe data beyond the day of interest. This is because the lowest 60 minute interval consumption level and the highest 60 minute interval consumption level could vary day by day in those cases, as indicated on figures A2 and A3. In the same season, the minimum value could vary tremendously as a result of changes in base load energy consumption. For example if a household purchased an additional refrigerator, the minimum base load electricity consumption would increase by two folds. To check this possibility, I first obtained the daily 60 minute minimum interval data for one year on 3 randomly selected households. Figure A2 indicates all the daily 60 minute minimum consumption values plotted over the entire year for those 3 selected households. We can observe that these minimum values experience minor fluctuations and a few major ones throughout the year, particularly in the summer. Major fluctuations could be a result of leaving the air conditioner on during the entire night where this is not a common practice for the particular household.

Figure A2 Change of Daily 60 minute Minimum Values



Similarly, daily 60 minute interval maximum consumption values were plotted over the entire year on different households selected randomly for the analysis on figure A3. Seasons appear to influence maximum consumption values, with highest values occurring in the winter. There are a few occasions in which these daily maximum values drop significantly while other days remain high. Such days with low maximum values perhaps indicate those days where residents were completely absent from the house.

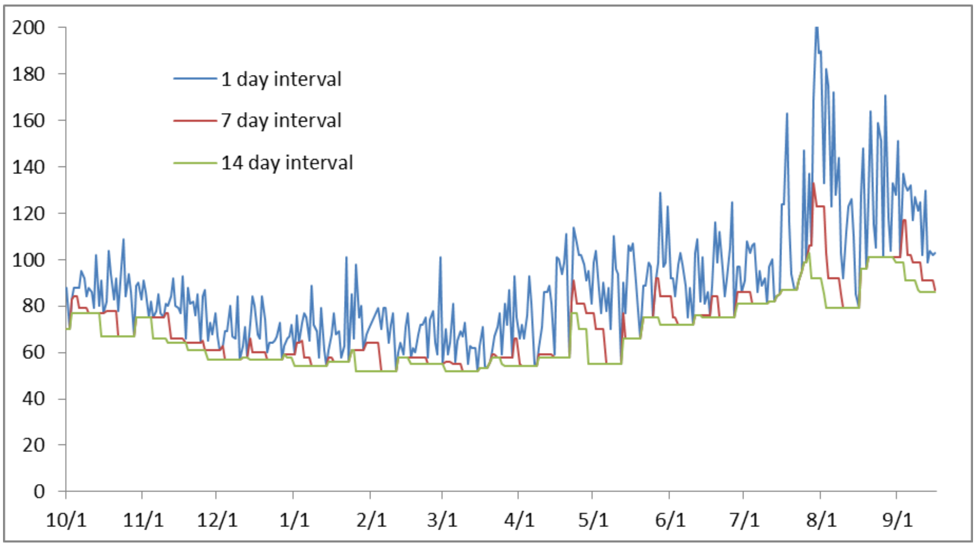
Figure A3 Change of Daily 60 minute Maximum Values



Figures A2 and A3 indicate the problem with simply using daily minimum and daily maximum values for computing e_{min} *and* e_{max}. Because of the dynamic nature of daily minimum values, as well as daily maximum values, I cannot select e_{min} or e_{max} by simply taking the minimum and maximum consumption values for the date of interest. We could obtain a better estimate for e_{min} *and* e_{max} by considering how daily minimum and maximum values have changed over the recent past days.

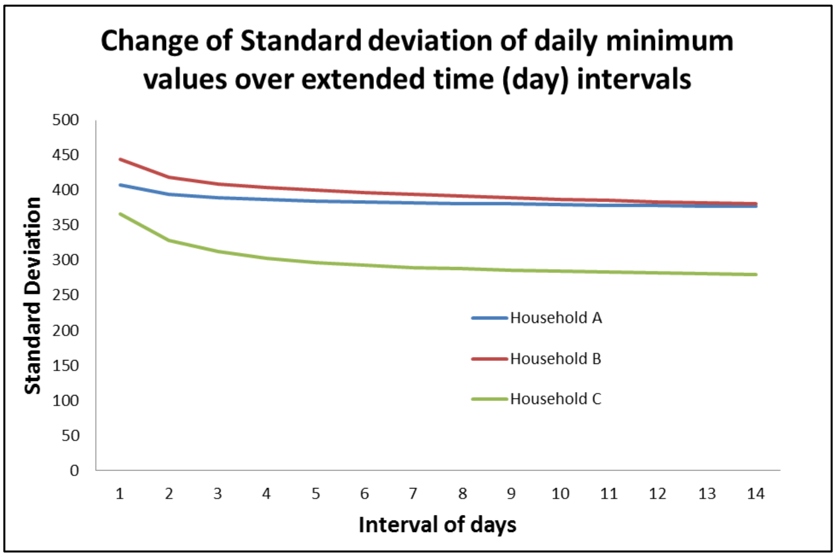
I expect that the minimum 60 minute interval consumption value over the previous 7 day span is a sound rule for computing e_{min}. To test this hypothesis, I plot the standard deviations of the year round data set on intervals ranging from daily minimum values to 14 day interval minimum values as indicated on figure A5. (ex. A 4 day interval minimum value will be the 60 minute interval minimum value for the interval ranging from the present day to 3 days back)

Figure A4 1 day, 7 day, 14 day interval minimum values plotted over a 1 year span for household A



First, I plot daily minimum data for the entire year using different day intervals. Figure A4 shows an example where I plot 1 day, 7 day and 14 day interval data. I then calculate the standard deviation of each data set and then plot each interval as indicated on figure A5. As we stretch the range of interval from 1 day to 14 days, the rough profiles shown on figure A2 begin to smoothen. As the patterns smooth, the standard deviation that measures the magnitude of fluctuations will gradually diminish.

Figure A5 Change of Standard Deviation of Minimum Values Over Extended Time (Day) Intervals



Standard deviations decrease rapidly initially and then reach a steady smooth value as I continue to expand the interval of days to around 5 to 7 days. Although the values continue a decline, expanding excessively could conceal the seasonal bias that we need to incorporate. Therefore, I select the minimum value of the latest 7 days as the necessary measure to find $e_{min.}$

To obtain the appropriate maximum value, I first plot daily maximum values of the entire year using different day intervals. Figure A6 demonstrates an example but I only display the summer time for a better distinction between the curves. I plot standard deviation of the year round data set on intervals ranging from daily maximum values to 14 day interval maximum values as shown on figure A7. In this situation, the average value over each daily maximum value is used. As I extend the interval from 1 day to 14 days, the patterns indicated on figure A3 smoothen. The change in the roughness of patterns on figure A3 as I extend the interval days, is captured by the changes in standard deviation of those data sets.

Figure A6 1 day, 7 day, 14 day interval maximum values plotted over a the summer for household A

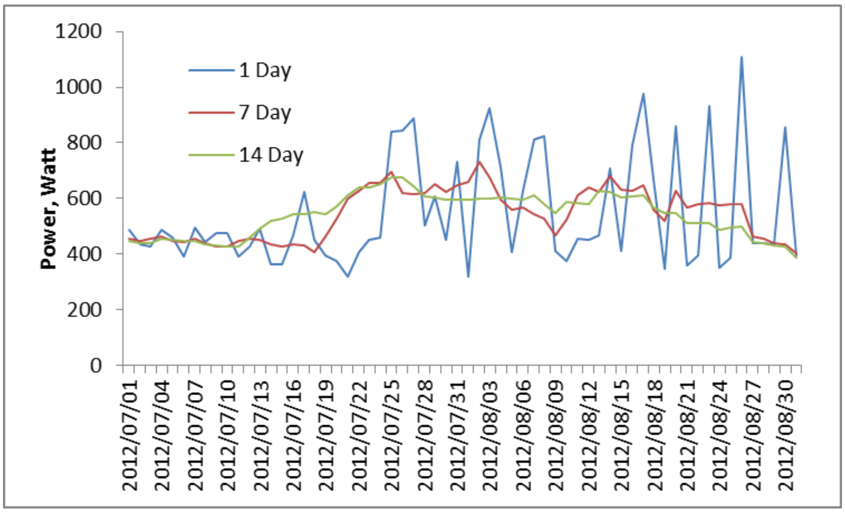
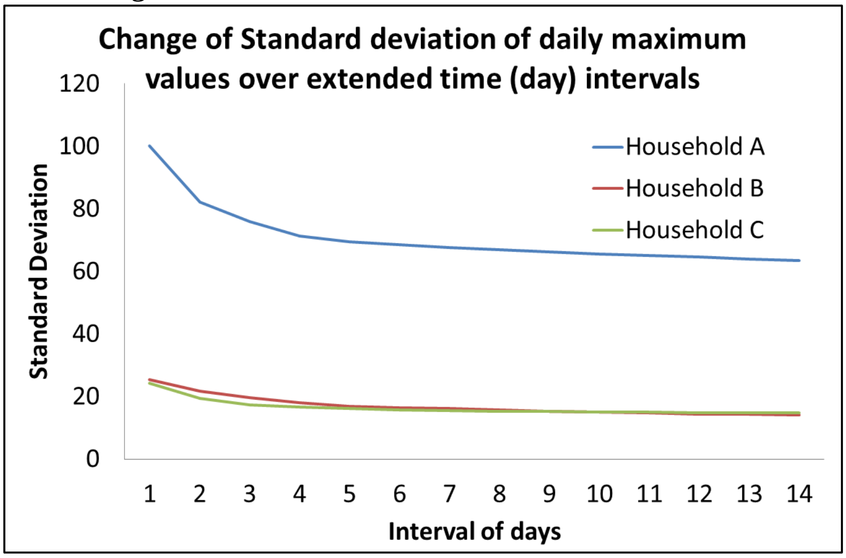


Figure A7 Standard deviation of maximum values



Also in this situation, standard deviations appear to flatten from the 7 day period. Although the values continue a decline in a smoother manner, extending excessively may conceal the seasonal bias we need to incorporate. Therefore, I select the 7 day average value of each of the daily 60 minute interval maximum consumption values as the necessary measure to find e_{max}..

APPENDIX B

For the purpose of confirming the accuracy of occupant detection algorithm, a dummy experiment was conducted at the author's housing unit. This single occupant household is a single room apartment unit in a 3 story reinforced concrete building located 5 kilometers away from the actual data site of Kashiwa-no-ha. An identical meter used for the households in Kashiwa-no-ha was installed and connected to the distribution board of the housing unit. Measurements were also in 10 minute intervals and the duration of this experiment was between November 9th, 2012 and November 22nd 2012.

I kept a record of the exact time I left and returned to the house. For the purpose of this research, the hours between 10AM and 6PM were considered. All minutes were rounded up the next hour.

The number of hours in which l_{it} was below 1 were compared with actual number of hours in which the resident (myself) was absent from the house. The numerical values displayed on this figure below represent each l_{it}. The highlighted cells indicate the hours in which I was absent from the house.

Figure B1

Dates	Time of Day (hours from 10AM to 6PM)							
	10	11	12	1	2	3	4	5
2012/11/09 Fri	4	4	2	1	1	1	1	1
2012/11/10 Sat	1	1	1	1	1	1	1	1
2012/11/11 Sun	1	1	1	1	1	1	2	1
2012/11/12 Mon	1	1	1	1	4	4	5	4
2012/11/13 Tue	1	1	1	1	1	1	1	1
2012/11/14 Wed	3	4	3	1	1	1	1	4
2012/11/15 Thu	1	2	3	1	1	1	1	1
2012/11/16 Fri	3	3	1	1	1	1	1	1
2012/11/17 Sat	1	1	1	1	1	1	1	1
2012/11/18 Sun	1	1	1	1	2	1	2	3
2012/11/19 Mon	9	12	2	1	1	1	2	9
2012/11/20 Tue	1	1	2	1	1	1	1	1
2012/11/21 Wed	5	2	2	1	1	1	2	3
2012/11/22 Thu	1	1	1	1	1	1	1	1

Drawing up from the chart on figure B1, the table below indicates the accuracy of this algorithm on detecting residence occupancy. I decided to judge the algorithm's accuracy based on the correctness of predicting 'absent' when the occupant should have been absent. The cells colored in light brown indicate the hours in which the occupant (I) was outside of the house. If the number indicates a 1, then the algorithm indicates the occupant was outside of the house. On 6 occasions out of 85 selected hours where the occupant was in fact absent from the house, the algorithm presented a mistake. Thus, on 92.9% of the times, the algorithm is correct.

Table B1

Date	Absent	Algorithm	*Difference*
2012/11/09 Fri	5	5	0
2012/11/10 Sat	8	8	0
2012/11/11 Sun	8	7	1
2012/11/12 Mon	4	4	0
2012/11/13 Tue	8	8	0
2012/11/14 Wed	5	4	1
2012/11/15 Thu	5	5	0
2012/11/16 Fri	6	6	0
2012/11/17 Sat	8	8	0
2012/11/18 Sun	5	5	0
2012/11/19 Mon	5	3	2
2012/11/20 Tue	8	7	1
2012/11/21 Wed	3	3	0
2012/11/22 Thu	7	8	1
		Accuracy	92.9%

I have provided this brief analysis as a proof for the occupancy detection methodology indicated in chapter 4.

Appendix C

Verifying E_{norm} and E_{shift}

As a way to check the algorithm's reliability, individual appliances were measured at the author's household. Each appliance was categorized into each category below.

Table C1 list of appliances monitored

	Base load	Regular	Temporal
Desktop Computer		✔	
Computer Display 1		✔	
Computer Display 2		✔	
Speakers		✔	
Printer			✔
Internet Modem	✔		
Internet Router	✔		
Air Conditioner		✔	
Refrigerator	✔		
Toaster			✔
Microwave			✔
Washing Machine			✔
Hair Dryer			✔
Battery Chargers			✔

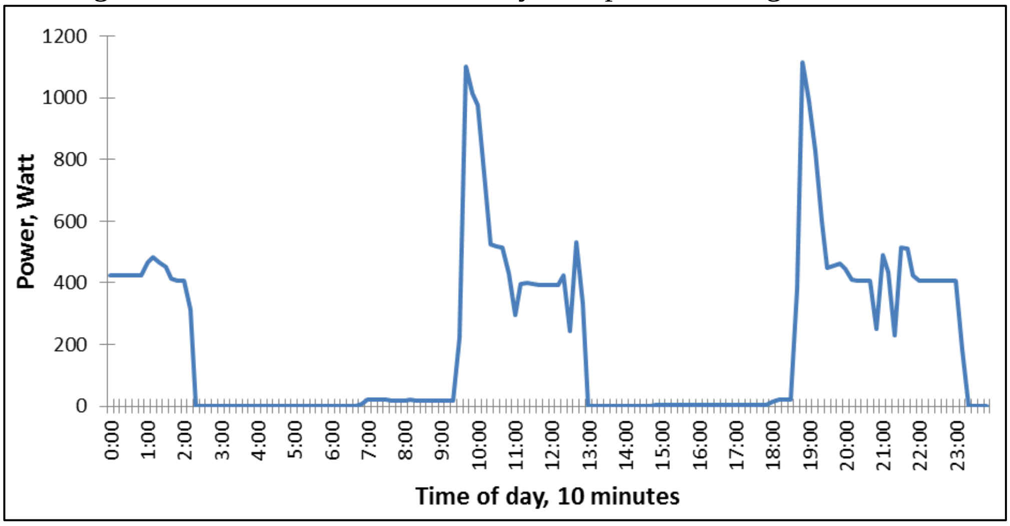
The total consumption under 'Regular' is equal to E_{norm} and the total consumption under 'Temporal' is equal to E_{shift}. I measured electricity consumption for 3 weeks between November 11 and December 12 of 2012. Running the identical algorithm on total electricity consumption for the entire household, the following results were obtained.

Table C2

	Measured Enorm (Wh)	Estimated Enorm (Wh)	Difference (Wh)	Measured Eshift (Wh)	Estimated Eshift (Wh)	Difference (Wh)
11/22	73	0	73	19	0	19
11/23	2486	2666	-180	18	461	-443
11/24	1321	1084	237	15	366	-351
11/25	961	770	191	73	241	-168
11/26	1395	1501	-106	15	349	-334
11/27	535	421	114	0	65	-65
11/28	1213	1196	17	33	115	-82
11/29	849	720	129	0	139	-139
11/30	1299	1170	129	134	100	34
12/1	2383	2309	74	0	310	-310
12/2	356	0	356	101	0	101
12/3	1757	1833	-76	55	91	-36
12/4	1597	1279	319	0	154	-154
12/5	440	236	204	51	6	46
12/6	366	344	22	144	58	86
12/7	930	803	127	0	60	-60
12/8	1937	1491	446	103	574	-470
12/9	2094	1893	202	38	367	-329
12/10	1365	939	426	73	297	-223
12/11	1389	1261	128	110	243	-133
12/12	45	0	45	0	5	-5
	24789	21912	2877	983	3998	-3015
	Error ratio (%)		12%	Error ratio (%)		307%

While E_{norm} had a fairly low error ratio at 12%, E_{shift} showed an unacceptably large error of 307%. One of the reasons why this happened was most likely due to the air conditioner. When we simply assume E_{shift} as consumption that are above a certain level (e_{basic}), we ignore the fact that not all E_{norm} consumptions are completely flat. The air conditioner experiences a sharp peak in electricity consumption at the beginning of its energy consumption. Stable levels of electricity consumption are only reached after a certain lag which most likely corresponds to the moment in which the room temperature reaches desired temperature.

Figure C1 Air conditioner electricity load profile of target household



After the initial stage of consumption that lasts nearly 60 minutes, the load profiles settle. The level of stable electricity consumption at 10 minute intervals appears to stay around 400 watts. I now calculated the total consumption that resulted from the initial peak from the air conditioner's electricity consumption for the 3 week period. The sum of all initial peaks consumption above the 400 watt level was calculated 2,925 Wh. This value nearly corresponds to the difference between measured and estimated E_{norm} and E_{shift}. With this value of consumption exchanged between E_{norm} and E_{shift}, the error ratio is reduced to convincing numbers. E_{norm} improved to a 0.2% error ratio from 12% and E_{shift} improved to a 9% error ratio from 75%.

Table C3 Adjusted estimates for E_{norm} and E_{shift}

	E_{norm}	E_{shift}
Measured (Wh)	24789	983
Adjusted Estimations (Wh)	24837	1073
Difference (Wh)	48	90
Error Ratio (%)	0.2%	9%

The results show that, as long as the initial peak consumption pattern observed from the air conditioner is considered as a part of E_{norm} instead of E_{shift}, the range of errors for E_{norm} and E_{shift} is small. This also indicates that as long as the air conditioner is running on stable mode after the peak, the accuracy of this methodology is kept quite high. Also in this particular household, the usage under E_{shift} was particularly small. Therefore, the absolute error value was a large portion of the entire E_{shift} value. At this moment, we intend to continue to use this algorithm for estimating E_{norm} and E_{shift}. In households that have countless combinations of electricity appliance usage, we simply cannot single out this peak behavior from total household electricity load profiles.

AppendixD

Table D1 List of Living Pattern Regularity Test

Meter ID	Living Pattern Type A	B	C	D	Family Type
O09K0003	2	1	1	1	Couple 1 Child
O09K0004	2	0	2	1	Couple 1 Child
O09K0009	3	0	2	0	#N/A
O09K0012	0	0	1	4	#N/A
O09K0013	0	0	0	5	#N/A
O09K0026	0	0	1	4	#N/A
O09K0027	3	1	0	1	#N/A
O09K0029	5	0	0	0	Couple No Children
O09K0030	0	1	0	4	#N/A
O09K0031	1	2	1	1	Couple No Children
O09K0032	0	0	0	5	Couple No Children
O09K0039	0	0	1	4	Couple, 1 Child, Father, Mother
O09K0042	0	0	0	5	Couple No Children
O09K0045	2	0	0	3	Couple 1 Child
O09K0056	4	1	0	0	#N/A
O09K0057	0	0	0	5	#N/A
O09K0060	0	0	2	3	Couple No Children
O09K0062	0	0	1	4	Couple 1 Child
O09K0063	0	0	0	5	#N/A
O09K0067	2	1	0	2	#N/A
O09K0068	0	0	1	4	#N/A
O09K0072	0	1	0	4	#N/A
O09K0076	5	0	0	0	Single
O09K0078	1	2	0	2	#N/A
O09K0084	5	0	0	0	#N/A
O09K0086	0	1	0	4	#N/A
O09K0088	4	1	0	0	Couple No Children
O09K0091	1	0	1	3	Couple No Children
O09K0094	0	0	0	5	Couple 1 Child
O09K0096	0	0	0	5	Couple 1 Child
O09K0099	0	0	2	3	Couple, No Children, Mother in law
O09K0100	2	0	1	2	Single, Mother
O09K0101	0	0	0	5	Couple 1 Child
O09K0108	5	0	0	0	Couple No Children
O09K0109	0	0	1	4	#N/A
O09K0110	5	0	0	0	#N/A
O09K0111	0	0	1	4	#N/A
O09K0113	5	0	0	0	#N/A
O09K0114	2	0	3	0	Couple No Children
O09K0118	2	2	0	1	Couple 1 Child
O09K0121	0	0	0	5	#N/A
O09K0122	0	0	1	4	Couple 1 Child
O09K0123	0	0	2	3	#N/A
O09K0124	0	1	0	4	Couple 1 Child
O09K0125	0	0	0	5	#N/A
O09K0126	5	0	0	0	Couple No Children
O09K0127	3	0	2	0	#N/A
O09K0128	0	1	2	2	Couple 2+ Children

(continued)

O09K0129	4	0	0	1	Couple No Children
O09K0132	5	0	0	0	Single
O09K0133	2	1	2	0	Couple 1 Child
O09K0135	1	0	0	4	#N/A
O09K0137	2	0	0	3	Couple No Children
O09K0138	0	0	0	5	#N/A
O09K0142	0	0	0	5	#N/A
O09K0143	2	0	0	3	Couple 1 Child
O09K0144	0	0	1	4	Couple 1 Child
O09K0147	0	0	1	4	#N/A
O09K0148	1	0	0	4	#N/A
O09K0150	1	0	1	3	Couple 2+ Children
O10E0431	4	1	0	0	Couple No Children
O10K0153	0	0	0	5	#N/A
O10K0162	2	0	0	3	Couple No Children
O10K0167	0	0	2	3	Couple 2+ Children
O10K0168	0	0	0	5	#N/A
O10K0183	5	0	0	0	Couple No Children
O10K0199	2	1	0	2	#N/A
O10K0201	0	0	0	5	Couple No Children
O10K0211	0	0	0	5	Couple 1 Child
O10K0220	5	0	0	0	Couple No Children
O10K0226	0	1	0	4	Couple 2+ Children
O10K0227	0	0	0	5	Couple No Children
O10K0230	0	0	0	5	Couple 1 Child
O10K0236	3	0	2	0	#N/A
O10K0246	0	1	1	3	#N/A
O10K0247	3	0	1	1	#N/A
O10K0250	0	0	1	4	#N/A
O10K0264	5	0	0	0	Couple No Children
O10K0265	0	0	0	5	#N/A
O10K0271	0	0	0	5	#N/A
O10K0272	0	0	1	4	Couple 1 Child
O10K0274	0	1	1	3	#N/A
O10K0275	5	0	0	0	Couple No Children
O10K0283	1	1	2	1	Couple No Children
O10K0285	5	0	0	0	Couple 1 Child
O10K0296	0	0	0	5	Couple, No Children, Father, Mother
O10K0336	3	0	0	2	Couple No Children
O10K0346	5	0	0	0	#N/A
O10K0389	2	1	1	1	#N/A
O10K0396	0	0	0	5	Couple 1 Child
O10K0420	0	1	0	4	Couple 1 Child
O11C0898	0	0	1	4	#N/A
O11C0900	2	0	1	2	#N/A
O11C0901	1	0	1	3	#N/A
total count	18	0	0	43	33