ANALYZING THE POTENTIAL OF DEMAND RESPONSE IN RESIDENTIAL BUILDINGS

by

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ABSTRACT

SUMEDH MILIND HALBE. Analyzing the Potential of Demand Response in Residential Buildings. (Under the direction of DR. BADRUL CHOWDHURY)

Due to increasing penetration in renewables in the grid, it has become increasingly necessary to provide a balance between supply and demand. Demand side management, especially in residential buildings, could play a vital role in providing this balance. They have a massive untapped potential which could support the grid of the future. These flexible loads could also help enhance the grid reliability and support system stability. A 500-house residential building system is created and simulated using a tool called GridLAB-D to estimate the potential of demand response from these residential buildings. The detailed model has the capability of controlling each individual end-use appliance. Impacts of rebound effects and methods to mitigate these rebound effects are also discussed. The primary aim of this thesis is to provide a methodology for estimating various value streams of demand response. Apart from peak reduction, demand response can provide several other functionalities. To assess the benefits, the residential building system is connected to an IEEE distribution test system. Finally, a framework is developed for evaluating the feasibility, viability, costs and benefits of the demand response programs.

DEDICATION

I would like to dedicate my master’s thesis to my parents.

ACKNOWLEDGMENT

I would like to express my sincere gratitude to my advisor Dr. Badrul Chowdhury for his continuous support during my master's study and research, for his encouragement, patience, humility and unrivalled knowledge. I was grateful to have him by my side throughout this two-year journey. Without his inputs and constant support, this work would have been impossible. Dr. Chowdhury not only helped me with the technical guidance, but he also helped me grow as a person.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

The complex electricity network requires a constant real-time balance between supply and demand to maintain the system stability and reliability. The conventional method to provide the balance is to use the traditional generators for ramping their power up or down as per the grid requirement. Due to an increasing demand in recent years, rapidly increasing fuel costs and penetration of variable energy renewable resources, which are often unpredictable in nature, the challenge to provide this grid balance has become more complex . The stochastic nature of these variable energy resources introduces an increased need for operating reserve requirements on the system. The frequent ramping of conventional thermal generation reduces the system inertia affecting the stability of the system and affects the traditional method of providing reserves.

Currently, the demand side is being underutilized, and the participation of these customers can bring in considerable changes in the electricity demand requirements. As the penetration of renewable energy generation increases in the generation portfolio, it becomes less controllable. Hence, these emerging technologies such as demand response (DR), micro-grid and virtual power plants would provide cost effective control for maintaining the demand and supply balance.

1.1 Need for Demand Side Management

1.1.1 Electricity Consumption History and Trends

In 2017, 25570 TWh electricity was generated globally [2]. During the same year electricity generation increased by 3.1% and the increase in demand was faster than the generation. Electricity demand growth is associated with various factors like climate and economic development. Since the inception of industrial age, economic development has been rapid. Hence, the requirement for electricity has been increasing. In 1973, global electricity consumption was highest in the industrial sector followed by residential sector and this can be seen in the Figure 1 below. The electricity consumption in all sectors except residential and commercial sector has decreased since then. It can be observed by a comparison of Figure 1.1, Figure 1.2 and Figure 1.3 that energy consumption in residential sector was highest and hence the focus of all energy management programs should be on the residential sector.

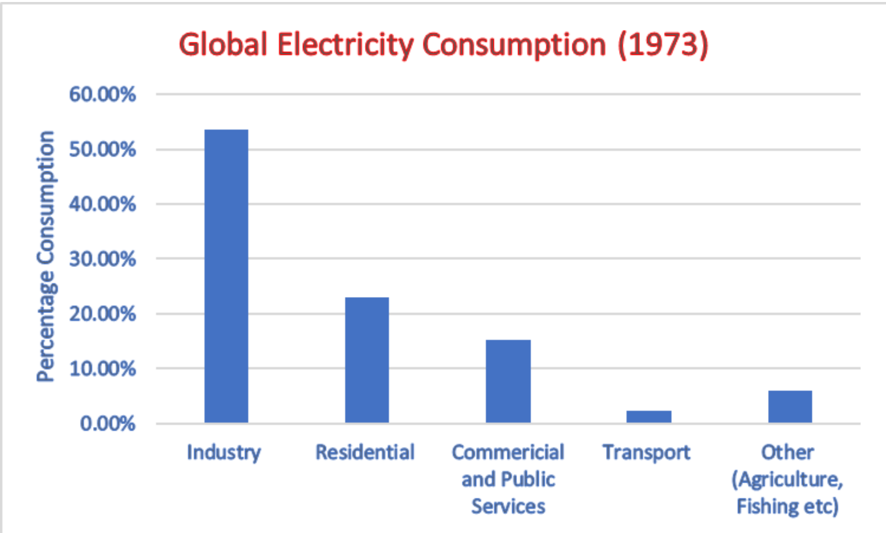

FIGURE 1.1: Sector-wise global electricity consumption for year 1973 [2]

Figure 1.2 shows the data for year 2015. Hence, to reduce the overall demand growth, the amount of electricity consumed by residential and commercial sectors should be decreased. The focus of this thesis is completely on the residential sector. The invention of new communication technologies, smart grids and awareness within the consumers has made this kind of demand side management possible.

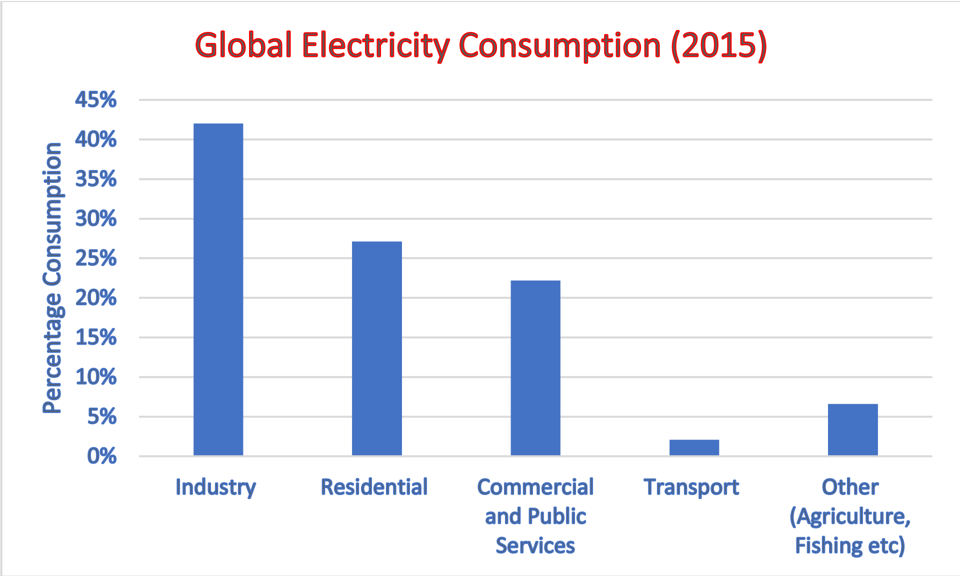

FIGURE 1.2: Sector-wise electricity consumption for year 2015 [2]

The United States is the second largest consumer of electricity in the world. It is estimated that by 2040, the demand for electricity in the US will rise by 18% [2]. The electricity utilization in the USA is different when compared with the global utilization. Residential sector accounts for the maximum electricity consumed. The primary reason for this is the high standard of living in the US and extreme climate experienced by different regions. As for the high standard of living, the consumption levels in Figure 1.4 suggest that the new end uses have been increasing in the recent years. It is evident from the consumption levels of space heating and cooling, that the climate is a major factor responsible for driving these energy consumption levels up.

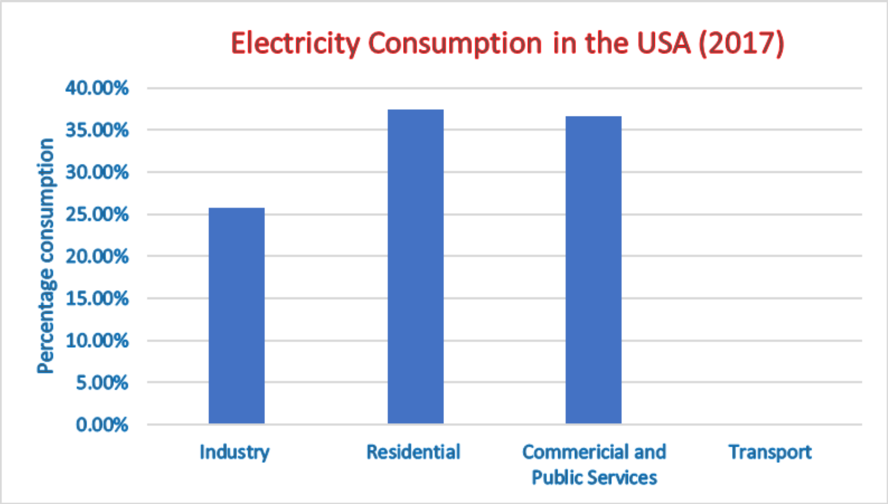

FIGURE 1.3: Sector-wise electricity consumption in the USA [3]

1.1.2 Generation Mix in the US

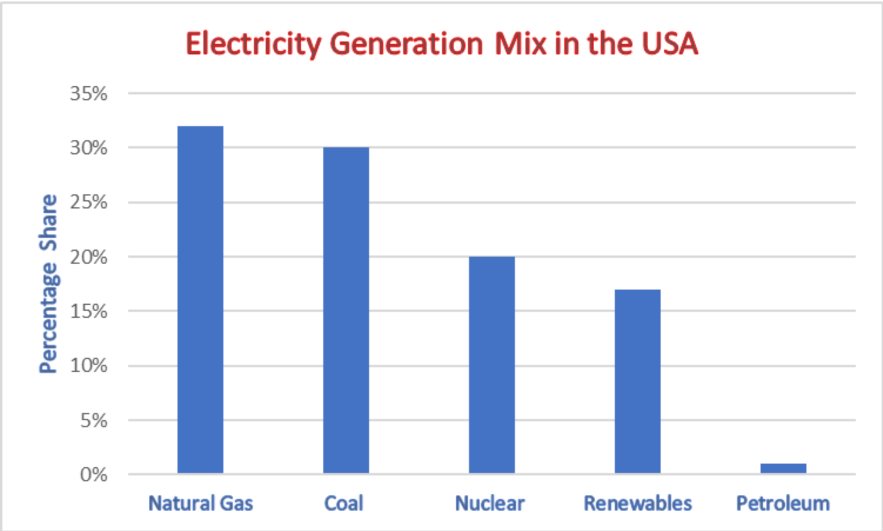

FIGURE 1.4: Electricity generation mix in the USA [3]

Most of the electricity generated comes from fossil fuels. Only 17% of the total electricity is generated from renewables which includes hydro power as well. Fossil fuels, when used to generate electricity, emit carbon dioxide, and are responsible for creating global issues such as climate change in recent years. Apart from the environmental concerns, energy security and dependence on foreign countries for resources is also a key driver for reducing energy consumption.

1.1.3: A Typical Utility's Generation Mix

Electricity cannot be stored economically, indicating that the supply of electricity must balance the demand at any given moment. The marginal cost of supplying these needs is variable as the demand fluctuates. Cost of electricity changes accordingly, although most of the customers are charged a flat rate which represents the average cost of production. This leads to inefficient use of resources.

A utility or a generating company typically maintains a diverse generation portfolio. These generators are broken down primarily as base generators, intermediate generators and peaking generators. The base generators are typically cheapest and slow ramping units, for example coal and nuclear. These base generators run constantly as they provide power at the cheapest rate. When the demand is not being met by these base load plants, intermediate generators are dispatched which have a higher price and higher ramping rate than base load plants. During the peak periods, most expensive generators are dispatched. They have a very high ramp rate as well as high cost of generation. These plants are used only during peak periods and are on standby during the off-peak period.

For any utility, around 60% generation capacity is supplied by the base load plants. Around 15-20% capacity is supplied by the intermediate plants and the remaining 20-25% capacity is supplied from the expensive peaker units [4]. If the peaks are reduced, the need to dispatch these peaker plants would be reduced as well. A 20% reduction in demand would completely avoid use of these expensive peaker plants. Table 1 below describes Duke Energy Carolina's generation portfolio based on dispatchability of various generating units.

TABLE 1.1: Duke Energy Carolinas generation mix

Resource Type	Percentage of Total Capacity
Base	56%
Intermediate	7.5%
Peaking Renewables and Storage	15%
Conventional Peaking Units	21.5%

1.2: Demand Side Management

Increasing demand has called upon the need for demand side management (DSM) programs. These are the methods in which the end user participates and helps in lowering or shifting the demand. Classification of DSM programs based on the duration and impact on the customer processes is shown in Figure 1.5. From the utility's perspective, the program should have a long-term impact making energy efficiency the most suitable form of DSM, but, from customers' point of view, short spanned programs would have the least impact on their processes. The changes involved in energy efficiency are permanent changes, and these changes include replacing the older equipment with new ones, such as replacing old pumps with newer efficient pumps, or improvements on the physical properties of the building, like adding insulation to the building or replacing single pane windows. These changes permanently optimize the system, and hence, are considered the most effective means of energy savings by the utility, although, this would require heavy investments from the customers. Hence, these programs are less likely to be adopted by the customers without any provision for incentives from the utility. Market DR consists of real time pricing, price signals and incentives [5]. Market DR is usually done on a day ahead schedule in the day ahead market; an exception is real time pricing which takes place in the spot market [5]. In market DR, the participants could react by changing their load pattern in accordance with the market prices. Examples are charging water heaters during valley hours and turning them off during peak periods. Limited customer elasticity and situations not associated with the price of electricity can lead to load shedding for relieving the stresses on the grid. Thus, physical DR is used in the emergency situations. Direct load control is an example of physical DR program. Physical DR lasts for a shorter duration and sends out mandatory signals for load curtailment. A combination of the two would help in the smooth and optimal functioning of the grid.

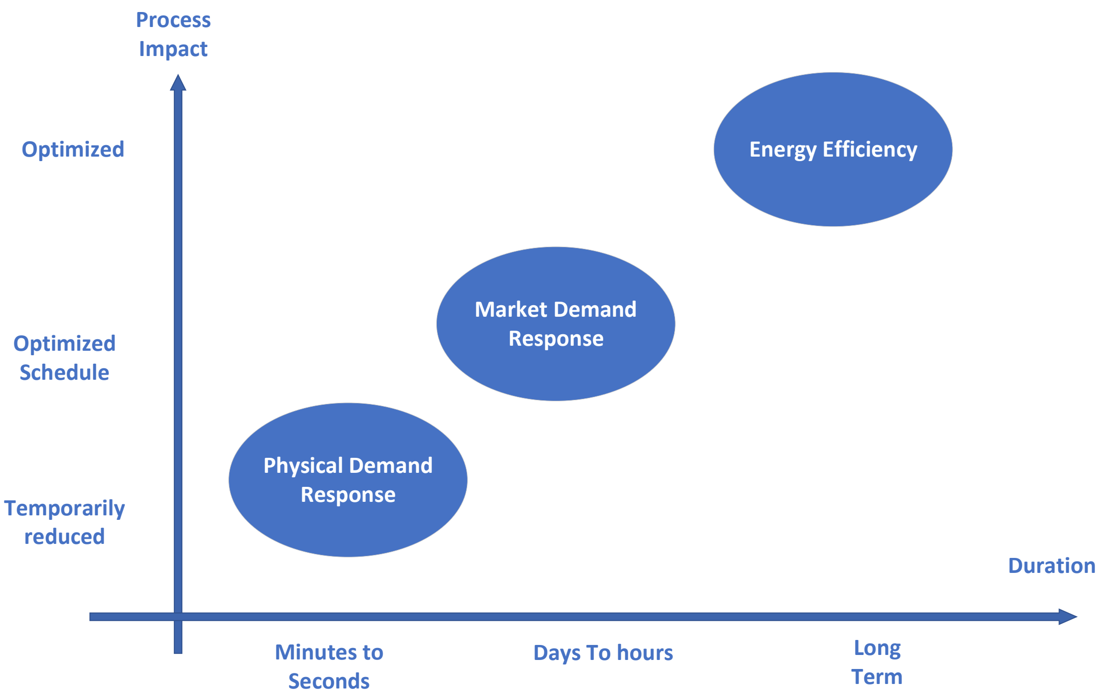

FIGURE 1.5: Demand side management programs classification [5]

1.2.1: Energy Efficiency and Demand Response

EE and DR are closely related. Both provide a means of reducing demand growth and utility bills, although, there are differences in the way these resources are utilized. Energy efficiency brings in permanent changes to electricity consumption by installing or replacing older appliances/devices with new and more efficient devices that reduce the amount of energy required to perform its designated function or service [6].

DR refers to a change in electric consumption pattern by end-use customers from their normal pattern in response to changes in price of electricity over time, or to incentive payments designed to promote lower electricity use at times of high wholesale market price or when system reliability is jeopardized [7].

1.3: Demand Response

The concept of DR in the US electric power industry can be traced back to mid-1890's. Initially, systems engineers and utility executives debated over the optimal pricing of electricity which was called as Hopkinson's demand charge or time-of-day differentiated rates back then [8]. The initial motivation behind load management was driven by the increasing air conditioning in the system which caused sudden spikes and increased the peak to average ratio. In 1970s and 1980s with the help of integrated resource planning, utilities recognized the adverse impacts of system costs required for meeting peak loads and made load management as their reliability resource. The first load management programs developed in early 1970s were programs that directly curtailed/interrupted the end-use loads and the tariffs were received accordingly. The customer's sold the rights, but were not obligated to curtail some of their load in exchange to receive incentives [9].

In the mid-90's, a wave of reforms created restructuring of electric sector and markets were created to support competition. These markets were intended to create competitive wholesale and retail markets. However, many problems arose in these restructured markets, such as the California crisis in 2001, price volatility and spikes, reliability concerns during peak demand and failure to generate economic benefits to name a few. This led policymakers and stakeholders to focus on DR indicating that it is necessary for efficient functioning of electricity markets.

It was energy policy act (EPACT) 2005 that passed laws pertaining to DR removing unnecessary barriers to wholesale market for DR participation in energy, capacity and ancillary services markets by customers and load aggregators, at either retail or wholesale level. [10]. Hence, it was necessary for the utilities to assess the performance of DRs, if it is to be used for load reduction or to respond to system emergencies.

1.3.1: Types of DR Programs

Various DR programs have been implemented by electric utilities since its inception. The primary objective of all DR programs is to modify the consumption patterns of electricity of all end users by altering the timing, level of instantaneous demand and total electricity consumption. The customer can primarily react in three ways to achieve all the goals of DR. The first involves changing the consumption pattern by reducing energy usage during peak periods. This method involves some loss of comfort since end users must sacrifice their day-to-day activities. This method could include changing set-points of thermostats during peak periods. The second option involves load shifting. Customers may shift some of their operations from peak periods to off-peak periods such as, not using dryers or washers during peak periods, or curtailing the use of pool pumps during peak periods. The third method involves use of external sources such as energy storage or distributed energy resources, or a combination of both. This option will help customers utilize the energy from this external source during peak periods, thus reducing the grid demand.

DR programs are broadly classified as incentive-based programs and price-based programs. Incentive-based programs are further classified into classical DR programs and market-based programs. Classical DR programs are the oldest ones in which the utility has control of the participating customer's appliances and the utility could decide to turn off the appliances during peak periods. Direct load control and interruptible programs are sub-types of classical DR programs. Participating customers receive incentives or discount on their tariffs. Participants are asked to reduce a fixed amount of load and customers who don't respond can receive penalties.

Market based programs include demand bidding, emergency DR, capacity market and ancillary services market. Market based programs unlike classical DR are bi-directional programs. In demand bidding participants submit a specific bid for load reduction in the wholesale market, if the bid is accepted the participant must curtail the specified load for a certain duration or face a penalty. In emergency DR programs, during emergency conditions the participating are asked to reduce their loads and these customers are paid incentives upon doing so [11]. The participants in capacity market programs commit to providing pre-specified load reductions when system contingencies arise [11]. The bids are usually accepted in the day-ahead market. On unsuccessful participation the customers receive a penalty. Ancillary service market allows customers to submit bid in spot markets as operating reserves (spinning and non-spinning reserves). When customer bids are accepted, they are paid the spot market prices for their commitment to be on standby or paid with spot market energy price if load curtailment is required [11].

Price based programs are based on dynamic electricity rates in which tariffs are not flat, and so the rates vary following the real time cost of electricity. The price-based programs prevent customers from high consumption of electricity during peak times by inducing high electricity prices. The primary objective is to flatten the demand curve by inducing low prices during off-peak period and high prices during peak period.

The simplest form of price-based programs is the time of use rates. This program has rates segregated into two blocks: peak and off-peak period. This program reflects average cost of electricity during different periods. Critical Peak Pricing (CPP) rates includes a pre-specified high price of electricity superimposed on TOU rates or normal flat rates. CPP rates are used during contingencies or when the wholesale price of electricity is very high for a limited duration of hours or days in a year [11]. Extreme day pricing is like critical peak pricing, the only difference being the high price is in effect throughout the 24 hours of the extreme day [12]. In extreme day rates, CPP rates for both peak and off-peak periods are applied during extreme days, and a flat rate is used for other days. In Real Time Pricing (RTP) programs, customers are charged based on hourly fluctuating price which is reflected by the real cost of electricity in the wholesale market [12]. Real time prices are displayed on a day-ahead basis or hour-ahead basis.

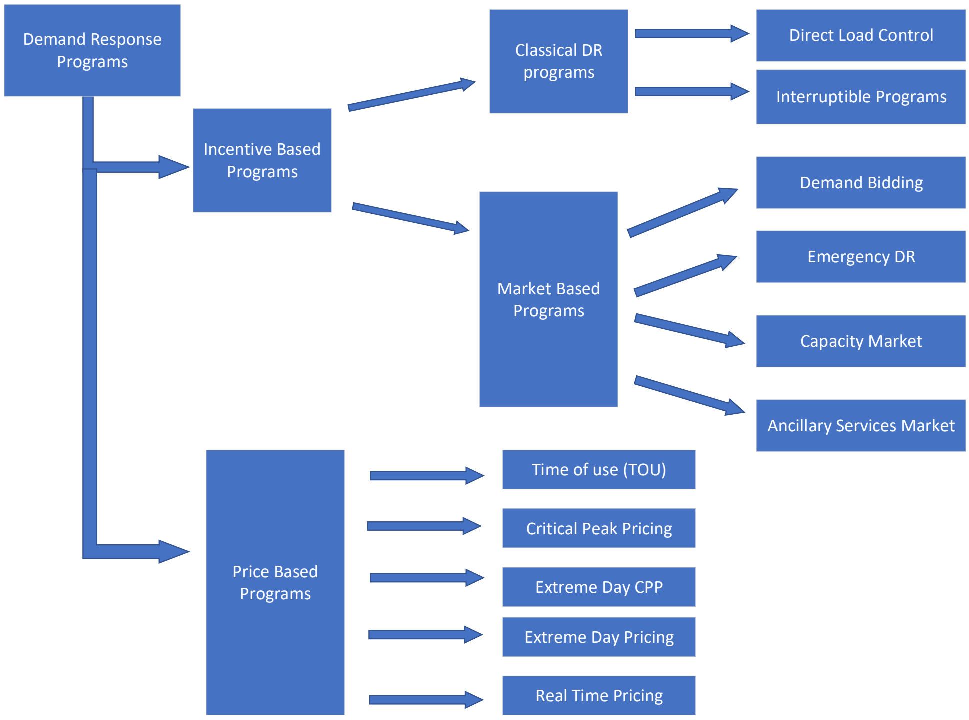

FIGURE 1.6: Types of various demand response programs

1.4: DR in Residential Sector

A typical house in residential sector includes single and multi-family homes. In residential sector, the breakdown of electricity as shown in Figure 1.7 below. It is evident that space heating and cooling requires maximum electricity, and account for more than 30% of the total electricity consumption, whereas small appliances and new end uses constitute the second highest consumer, contributing nearly 25% of the overall consumption. These new end uses include all the kitchen equipment, phones, hot tub pumps and all other small appliances. Residential energy consumption survey conducted by EIA, has classified these loads separately as new end uses.

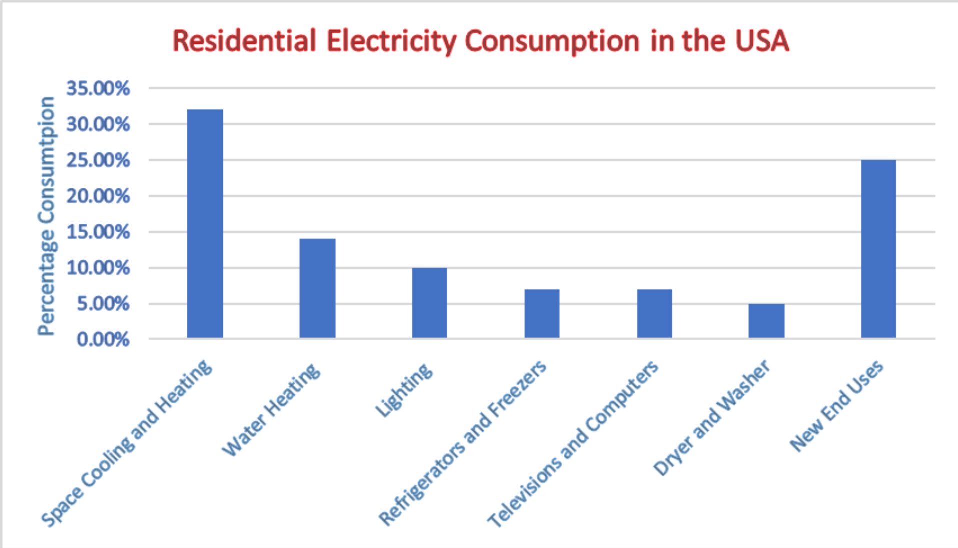

FIGURE 1.7: Residential electricity consumption in USA (2017)

In residential homes the most commonly used scheme is time of use (TOU) tariffs. These tariffs are set ahead in advance and are not a representation of the wholesale price of electricity at any moment. The TOU program is static DR strategy rather than a dynamic DR strategy.

Another such program which is one of the most widely adopted DR programs is direct load control of air conditioning units. In this program, switches are installed at the compressor of the HVAC unit and these switches are controlled either manually, remotely or by means of an under-frequency sensors [12]. Customers are provided with incentives after signing up for such DR programs. The attributes of a good DR strategy are its detection and acceptance by the customers. In the case of direct load control programs, sometimes the duration of DR is long enough to cause discomfort to the customers as the indoor temperature would become unbearable. This induces a decrease in the participation over time. These resources were later tested for short term responses, and by aggregating them, their potential participation in ancillary markets as operating reserves was tested as well. This short-term program was successfully implemented since most of the time, the DR event's duration was short enough to go unnoticed.

With the development of numerous communication devices and smart appliances in the residential buildings, the potential of aggregating these various small loads has increased. The benefits obtained can comprise of larger loads available for curtailment as well as increasing the duration of curtailment by sequential shedding of loads within a cluster of loads, by varying the response time from individual loads. The currently installed appliances have proprietary and independently operated communication protocols which reduces the visibility of aggregation. Although, there are pilots that can resolve this issue by creating a translator from one protocol to an appliance specific module [13]. These type of integrated platforms like home area network do exist but the relatively small benefit, discomfort for occupants and long payback period have prevented wide acceptance of these programs.

With the advent of programmable controlled thermostats (PCTs) they have been a leading technology in this field. Comprehensive studies have been conducted on PCTs with regard to the model and control of thermostatically controlled loads for a variety of aggregation algorithms and timescales of grid transactions [14] The PCT market is rapidly growing with shipments expected to grow from 1 million units in 2014 to 19.2 million units by 2023 [15]. These PCTs have demonstrated energy savings as well as they can be deployed in the DR programs.

Decreasing cost of communication technologies has increased the feasibility of several smart DR programs in the residential sector. The current adoption rate of DR in residential customers is fairly low, but the potential among this class hasn't been completely utilized. It has been estimated that residential customers only provide 17%

of today’s DR potential, although they have the potential of providing about 45% DR impacts in the achievable participation case [7]. The amount of total system peak reduction that can be expected from the residential customers in achievable participation case is about 8% whereas a full participation can create peak reduction of about 10% or 100GW [7].

1.5: Current status of DR in USA

DR is a critical resource for satisfying the country’s requirement of electricity. This will reduce the requirement for constructing new and expensive generation units by reducing the peak demand. Although, according to Federal Energy Regulatory Commission (FERC) report published in June 2009, A National Assessment of DR Potential, the status of DR programs utilized back then was less than a quarter of the total market potential for DR [7]. FERC staff collaborated with the stakeholders to develop the National Action Plan on Demand Response which provided the necessary actions for achieving the DR potential [7]. The Energy Independence and Security Act (EISA 2007) has set new standards or has improved upon the previous standards which ensures efficient working of appliances.

DR programs are being widely implemented in both regulated and deregulated markets. The first generation of DR programs were incentive-based programs in which the participants played a passive role. The utility had a direct control over the participant’s load. The second-generation DR programs included participation of regional transmission operators (RTOs) and Independent system operators (ISOs). The third-generation of DR programs includes involvement of price responsive DR in both wholesale and retail electricity markets [16]. Since the invention of advanced metering infrastructure (AMI), it has become easier for utilities to deploy the DR programs. The increase in DR adoption among all three classes of customers - residential, commercial and industrial has been on the rise. In 2014, the number of residential customers enrolled in DR programs were 8,603,402 which increased to 8,739,535 in 2016 [17]. The actual peak demand in residential sector increased from 3,147 MW in 2014 to 3,608 MW in 2016 [17]. The potential for peak demand reduction during this period increased as well. These statistics show the increase in DR adoption among all types of customers, especially residential customers.

Currently DR programs are offered by numerous RTOs/ISOs such as California ISO (CAISO), PJM-ISO, NY-ISO, NE-ISO to name a few. Even large utilities such as Duke Energy, Pacific Gas and Xcel Energy have started providing DR programs to their customers. Since the inception of DR programs, the number of participants has increased every year. ISO New England for example offers three incentive-based programs to its customers [18]. The customers are allowed to participate in day-ahead markets or real-time markets through these programs. PJM has separate markets for energy, ancillary services and capacity [18]. The programs offered by PJM differ by their dispatch process. In some of the programs, the participants have to dispatch during an emergency conditions whereas in others, the consumers are required to commit a certain capacity prior to the DR event. A qualified DR resource is eligible to participate in the wholesale market and provide ancillary services such as synchronized reserves, regulation reserves, or day ahead scheduling reserves. The minimum acceptable capacity for any participant to enrol in a DR program in PJM is 100kW [18]. NY-ISO has five different DR programs. The programs are incentive based DR programs as well some programs price-based DR programs which strictly pay for the energy. NY-ISO like PJM has DR program which allows participants to provide ancillary services. With help of web enabled services and advanced metering infrastructure it is possible for ISOs to collect real-time information from the consumers allowing them to participate in the real-time market. Even various utilities have their DR programs. For example, Xcel Energy and PG&E have a critical peak pricing and TOU based DR programs. Duke Energy Carolinas a vertically integrated utility has various DR programs, which include direct load control program as well interruptible programs and rate-based programs [18]. For residential customers there is only program available which enables customers to participate voluntarily and reduce their HVAC consumption during the peak periods.

1.6: Costs and Benefits of DR

For any program to be deemed to be successful, it is required that the program produces more benefits than the costs incurred to implement that program. In this section, the costs and benefits of DR are briefly discussed. For some components, the costs incurred by the utility, could be a benefit for the customer or vice-versa. Also, these costs and benefits would vary with the market structure [11]. A detailed explanation and methods for quantifying some of these costs and benefits are provided in chapter 5 of this thesis.

1.6.1: Costs of DR

Table 1.2 below provides a brief summary for the costs incurred by the program participant as well as the costs incurred at the system level.

TABLE 1.2: Costs of DR

Cost Bearer	Type of Cost	Details
Participant costs	Initial Costs	Enabling technologies such as smart thermostats, peak load controls.
		Establishing DR plans, customer training.
	Ongoing Costs / Event specific costs	Comfort / inconvenience costs
		Rescheduling costs, Loss of business activity

TABLE 1.2: Costs of DR (Continued)

Cost Bearer	Type of Cost	Details
		Fuel and maintenance costs of on-site generators
System costs	Initial costs	Metering and communication system upgrades such as AMI (advanced metering infrastructure)
		Billing system upgrades, equipment and software upgrades.
		Rebates on technology, training etc.
	Ongoing program costs	Administration costs

1.6.2: Benefits of DR

Table 1.3 below provides a brief summary of benefits obtained from the DR programs.

TABLE 1.3: Benefits of DR

Type of Benefit	Recipients	Details
Direct benefits	Participants in the DR programs	Financial benefits such as bill savings and incentives received from the utility
		Reliability benefits such as reduced risk of blackouts and forced outages
Collateral benefits	Some or all consumers	Reduced marginal costs/prices of electricity
		Reduced risk of market interventions such as price cap
		Avoided variable supply costs
	Utility, RTOs/ISOs or LSE	Avoided (deferred) capacity costs
		Avoided (deferred) transmission and distribution capacity upgrades
		Avoided energy costs due to better link between retail rates and marginal costs

TABLE 1.3: Benefits of DR (Continued)

Type of Benefit	Recipients	Details
		Reliability improvement due to diverse resources
Other benefits	Customers, utility, ISO/RTO and LSE	Option to manage electricity price where retail competition is not available
		Environmental benefits due to reduced emissions from peaking generators
		Energy independence and security as reliance on outside supply is reduced
		Elasticity reduces the market power

The next chapter will discuss the base case on which different DR strategies would be implemented.

CHAPTER 2: BASE RESIDENTIAL HOUSE MODEL

The methodology to evaluate the impacts of DR is represented in the Figure 2.1 below. First a residential system model is prepared using the data for a particular region. After building the model, different DR strategies are implemented and the impact of that particular strategy on the load is evaluated. After evaluating the impacts on the load model, the impacts on the distribution system are evaluated. Finally, various value streams generated from demand response are analyzed.

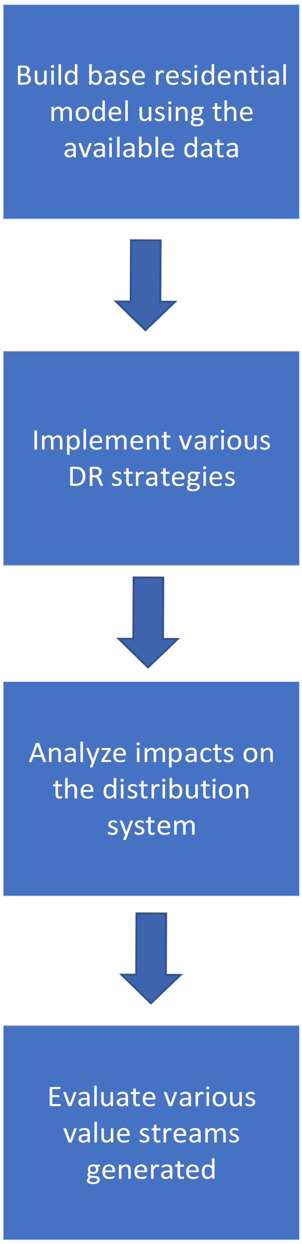

FIGURE 2.1: Framework for methodology

A 500-house residential building system is prepared as a base case. The system can act as an aggregator and respond to the signals from the ISO or the utility. The data and information for modeling was extracted from various credible sources to prepare a model which is close to a real system. Critical residential building parameters were obtained from Energy Information Administration's (EIA) residential energy consumption survey (RECS) which was carried out in 2015 [19]. The data available here is classified into various regions and climate zones. For this study, data from various regions was collected. For the final model, Charlotte, North Carolina was chosen to be the location. Hence, the data for south-Atlantic region was used. The assumptions made for creating a residential building model are described below in Table 2.1.

TABLE 2.1: Assumptions for residential building model

No.	Property	Value
1	Floor Area	1500-2000 Sq.Feet
2	Cooling Coefficient of Performance	4.0
3	Heating Coefficient of Performance	4.0
4	R-value of roof	30.0 DegF.sf.h/Btu
5	R-value of walls	13.0 DegF.sf.h/Btu
6	R-value of floor	19.0 DegF.sf.h/Btu
7	R-value of doors	5.0 DegF.sf.h/Btu
8	R-value of windows	1.66 DegF.sf.h/Btu

Floor area for average home size in U.S was obtained from RECS survey [19]. The R values decide the thermal integrity of the house. These values were obtained from the Department of Energy's standards on insulation for various climate zones [20]. It is assumed that all cooling appliances are all electric, whereas the heating appliances are either natural gas or electric [19]. The cooling COP of HVACs has a wide variation. The cooling COP here was considered as 4.0 after reviewing, seasonal energy efficiency ratios of various commercially available residential HVAC systems. The heating COP was assumed to be 4.0 as well. Each house is a detailed model and various end-use appliances are modeled separately.

2.1: HVAC Model

Thermostatically controlled loads (TCLs) are modeled as equivalent thermal parameters [21]. The ETP model is a series-parallel combination of active and passive elements analogous to an electric circuit [22]. These models are suitable for modeling and simulating residential as well as commercial buildings. The control hysteresis and heat balance dictate the pulse width and frequency of these TCLs. The power output changes between two fixed values. For residential HVACs without variable frequency drives (VFDs), the power level is either zero during the OFF state or rated power during the ON state since the control is ON-OFF control. The sizing of HVACs is based on the COP and floor area of the house. The HVAC output of each house will be different based on its floor area, setpoint preferences and COP of the equipment.

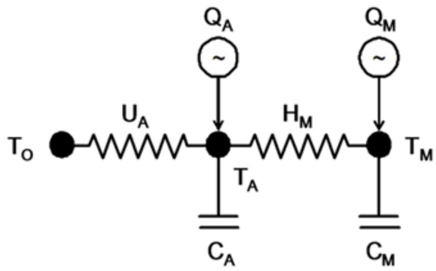

FIGURE 2.2: Equivalent thermal parameter model of a home in GridLAB-D

Here, conductance of the building is given as U_A and outdoor air temperature as T_o, T_A, is the indoor air temperature and T_M is the inner mass temperature. H_M is the conductance between inner solid mass and inner air. Q_A is the heat flux of interior mass, C_A is the thermal mass of the air and C_M is the thermal mass of building and Q_M is the heat flux of inner solid mass.

2.2: End Use Appliance Modeling

Each appliance was modeled with a heat fraction that is the amount of waste heat released while carrying out its desired function. These values were taken from Department ofEnergy's DOE2's inbuilt values and 2001 ASHRAE fundamentals handbook. The appliances that are modeled are:

1) Lights and Plug Loads
2) Water heaters
3) Clothes Dryer and Clothes Washer
4) Cooking Range and Microwave Oven
5) Dishwasher
6) Refrigerator

For each appliance commercially, available units were used for modeling. The models for each appliance are as described below.

1) Lighting and Plug Loads: Residential lighting is a combination of various types of fixtures. It was assumed that all houses were equipped with similar type of lights. CFLs have the average luminous efficacy hence for simplicity, it was assumed that all lights are CFLs. Average lux or lumens/m2 requirement for residential buildings is 150 [23]. Average luminous efficacy for CFL's 55 lumens/watt [24]. Using these values, required wattage was calculated using the equations below. The heat fraction from lights and plug loads is fixed at 30%. These heat fractions are accounted for additional heat gains. The power factor of the light depends on the type of the light but at aggregated level the power factor is fixed at 0.95 (lagging).

   1.1) Lighting requirement calculations:

$$Luminous\ intensity\ \left(\frac{watt}{m2}\right) = \frac{Luminous\ efficacy}{Luminous\ intensity} \qquad (1)$$

$$= \frac{150}{55}$$

$$= 2.7\,\frac{Watt}{m2}$$

$$= 0.25 \frac{watt}{ft2}$$

Average area of a house = 1750 Sq. Ft

$$Lighting\ requirement = Average\ area\ of\ a\ house * Luminous\ intensity \qquad (2)$$

= 1750 * 0.25

= 437.5 Watts.

1.2) Plug loads:

They consist of TVs, Computers and phone chargers. The power rating for each of the appliance is as given below.

a) TVs – 100 to 300 watts
b) Computers- 100 to 200 watts
c) Mobile Phone chargers- 5 watts x 4 = 20 watts

So, the total plug loads ranges from 650 watts to 1250 watts depending upon the number of televisions, computers and phones. A random uniform distribution was created using these value range. The demand profile for lights and plug loads was obtained from [25]. Figure 2.3 shows the normalized demand profile for lights and plug loads.

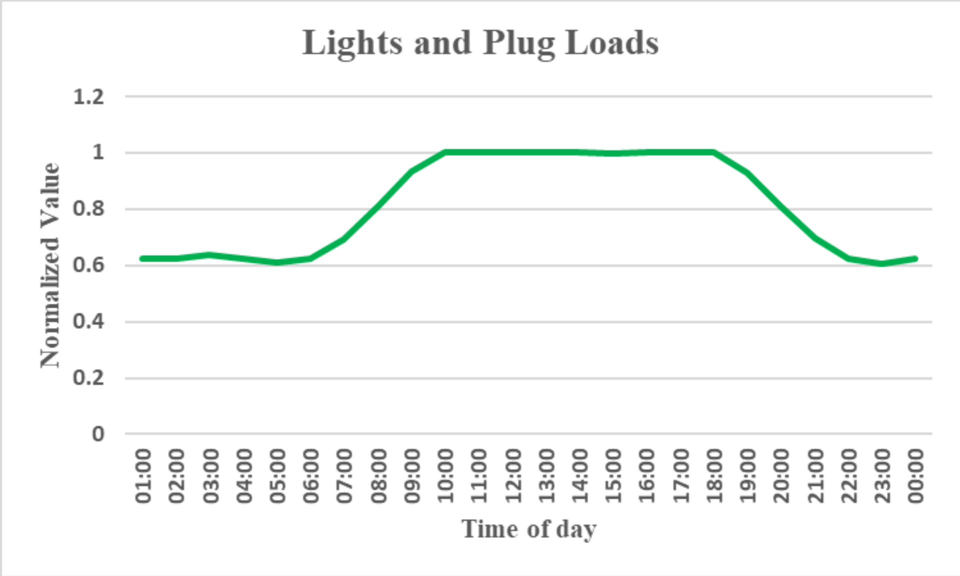

FIGURE 2.3: Demand profile for lights and plug loads

2) Water Heaters

The water heater sizing was based for a typical four-person family. A.O.Smith model of water heaters for a residential home was used [26]. The heating element capacity is 4.5 kW and the average tank size is 40-80 gallons. The specifications required for the model were heating element capacity, tank height, tank volume and were obtained from the A.O.Smith's brochure. The heat retention capacity of the water heater was calculated using equation (3). Where t_{ua} is the thermal coefficient. The thermal resistance R is considered as 12 ft^2·°F·h/Btu which is the minimum thermal resistance value recommended by DOE for water heaters [27].

$$t_{UA} = t_{SA} / R \tag{3}$$

The profile of hot water requirement for one day was obtained from ASHRAE's 90.2 standards [28]. Average consumption of hot water for one single day is 64.3 gallons and the profile are as shown in Figure 2.4. This percentage consumption from ASHRAE was converted to gallons per minute usage, and then the gallons per minute value for a single home was multiplied to a normal distribution to obtain a diversity in the consumption. Finally, a 30-minute schedule was created for the model.

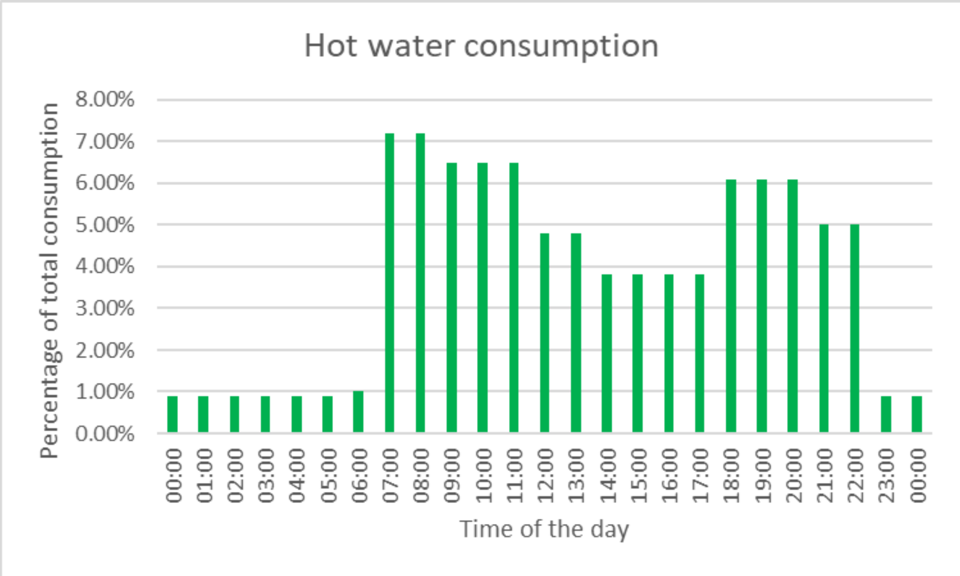

FIGURE 2.4: Hot water consumption for one day [7]

The inlet cold water usually enters the tank at the bottom part and the hot water is drawn from the top. This is a continuous process, i.e whenever hot water is drawn, cold water enters the bottom of the tank. The water heaters usually have two heating elements one placed at the top part of the tank and other one at the bottom. Heating is done by the lower element and the top element comes into action only when cold water reaches the top.

The two ways of modeling a water heater differ from each other depending upon the state of the tank at a moment [29].

I) One-Node Model: This is a simplified version of modeling a water heater. This model considers that the water inside the tank is at a uniform temperature.

II) Two-Node Model: This model considers water into two different slugs each at uniform temperature. The upper portion is the hot water which is near the heater's setpoint temperature, and the lower portion is the cold water which is near the inlet water temperature. This model has a better performance since it considers the thermal boundary between hot and cold nodes, and this helps in calculating the movement of that boundary as water is drawn or when head is added.

2.1. The mathematical model for water heater

$$CTW = Vol(gal) * \left(1 \frac{ft\text{^}3}{7.48(gal)}\right) * \ 62.4 \left(\frac{lbm}{ft\text{^}3}\right) * \ 1 \left(\frac{Btu}{lbm} * F\right) \qquad (4)$$

The thermal capacitance of the water is a function of the tank volume given by the equation 4 [29] above. The thermal conductance (U_A) which is conductance times surface area of the tank is calculated from the known R-values of the tank.

2.1.1. One Node Temperature model

The heat balance of the one node temperature model at water node is as given by equation 5. Here Q_e is the heat input rate, m is the mass flow rate, U_A is the conductance and CTW is the thermal capacitance. Tw is the temperature of water node, Ta is the temperature of ambient conditions and Tin is the temperature of inlet water. dTw/dt is the change in the water temperature. Equation 5 [29] shows the one node temperature model.

$$Qe - m * Cp * (Tw - Tin) + \ U * A * (Ta - Tw) = \ CTW * \frac{dTw}{dt} \qquad (5)$$

2.1.2. Two Node Temperature model

In the two-node mode, the time required to change the hot water column from an initial height of h_{int} to final height of h_{final} is given by equation 6 [29]. Here dh/dt is the temperature gradient and this is a function of mass flow rate.

$$T1 - T0 = \frac{1}{b} * \log\left(\frac{dh}{dt}\right) \qquad (6)$$

3) Clothes Dryer and Washer

G.E appliances [30, 31] models for dryer and washer were used. The power ratings of these appliances are 4.4kW and 0.5kW respectively. The average cycle duration for dryer and washer was obtained from [30, 31]. The power factor of these appliances is fixed at 0.95 (lagging).

4) Cooking Range and Microwave Oven

Cooking range is a resistive load and each heating element is cycled on or off using a TRIAC device. Like dryer and washer, commercially available models for residential use from G.E appliances were considered [32, 33]. Like the cooking range these devices are constant power consumers during their operating state. The power ratings for cooking range and microwave oven were chosen as 3 kW and 1 kW respectively. For cooking range, it is considered that 95% of the total energy is lost to surrounding as heat. Whereas for microwave, 65% of the total energy is considered as heat gains. The power factor of both appliances is fixed at 0.99 (lagging) [34].

5) Dishwasher

G.E appliances dishwasher was chosen with a power rating of 0.91 kW [35]. The cycle duration for dishwasher was chosen from [35]. For dishwasher it is considered that 55% of the total energy is lost as heat to the surroundings. The power factor of dishwashers is fixed at 0.96 (lagging) [34].

6) Refrigerator

Refrigerator was modeled along with a freezer. A freezer on top of the refrigerator was chosen for this purpose. A G.E appliance model with power rating of 0.8 kW was chosen [36]. According to G.E appliances newer refrigerator run almost continuously i.e they have almost 80 to 90 percent duty cycle. Load shape for south-eastern region was verified from [25]. Below Figure 2.5 shows the demand profile of a refrigerator. Although, it is assumed that the refrigerator runs throughout the day the amount of power consumed changes depending upon ambient weather conditions, number of door openings, heat gain from the addition of food to the refrigerator. These are the factors which would increase the inside temperature and force more refrigeration by having more cycles. The power factor of refrigerator is fixed at 0.95 (lagging).

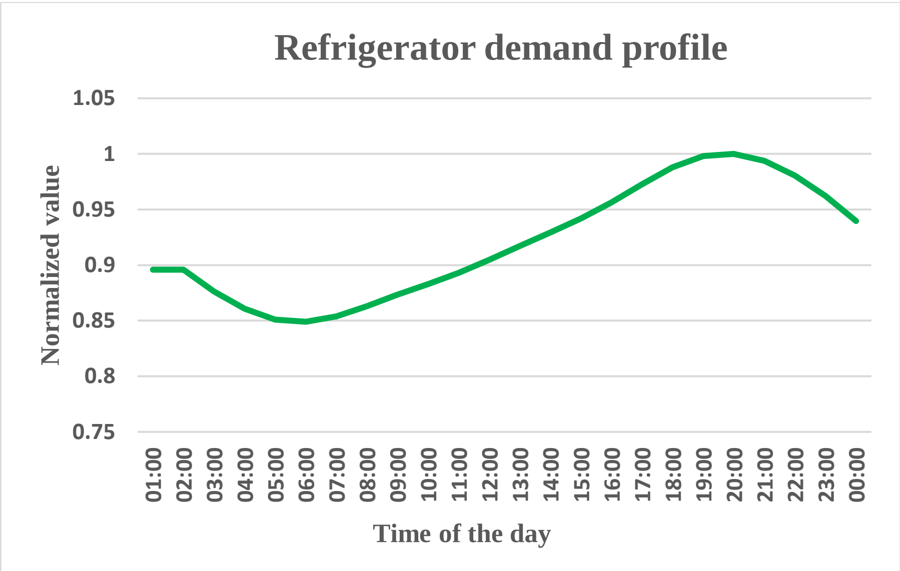

FIGURE 2.5: Refrigerator demand profile [25]

2.3: End-use Appliance Saturation

After selecting the models for all the aforementioned end-use appliances, saturation levels for each appliance for a particular region was selected from the RECS survey [19]. Saturation level here is defined as the number of houses equipped with an appliance out of total number of houses. For example, the saturation for refrigerators in the U.S is 99.5%. Table 2.2 below shows saturation percentages for the whole U.S, Southeast region of the U.S and South-Atlantic region of the U.S.

TABLE 2.2: Appliance saturation levels

No.	Appliance	U. S	South-East Region	South-Atlantic Region
1.	Electric Cooking Stove/Range	56.2%	66.8%	70.6%
2.	Microwave Ovens	96.2%	96.5%	96.5%
3.	Refrigerator	99.5%	99%	99.1%
4.	Dishwasher	67.5%	69.3%	71.0%
5.	Clothes Washer	82.5%	87.9%	88.9%
6.	Electric Clothes Dryer	64.5%	79.2%	80.42%
7.	Electric Water Heaters	46.2%	67.7%	71.4%

After selecting the appliances and their saturation levels in the residential building system, a schedule for their usage was necessary to be developed. This schedule is highly dependent upon human behavior. The frequency of appliance usage was collected from RECS 2015. A survey was created by the author of this study to get the specifics about the appliance use. All the details about the survey are explained in Appendix A.

2.4: Base Case Summer

A peak summer weekday was chosen for developing a base case. Since the output of HVACs is driven by the weather to get the maximum output, usually a day with maximum number of cooling degree days would be chosen. Degree days indicate how warm or cold a day is [3]. A comparison between mean average outdoor temperature with a standard defined temperature which is 65-degree F will give the number of degree days. Hence a day with very high cooling degree days will have a greater mean temperature. For this study, typical meteorological year (TMY3) weather data was used. TMY weather file for Charlotte region was obtained from the National Renewable Energy Laboratory's website [37]. TMY data sets are hourly values of local climate, solar irradiation for period of 1 year. Hence, after observing the TMY files a day with maximum mean temperature was chosen. As seen from the Figure 1.7 above HVACs constitute a large portion of the total demand. Indicating that the demand from HVACs will drive up the overall demand if all other appliances are being used at same rate on other days as well.

As seen from FIGURE 2.6 below, various inputs such as weather, time, geographical location, residential house models, end-use appliance models explained in previous section are given as inputs to the solver. This Solver is basically a complex algorithm which has millions of differential equations for each object in the system. This solver is event driven solver and is based on the states of the system and not time [38]. The states are then synchronized with time using a clock to obtain a time-series output.

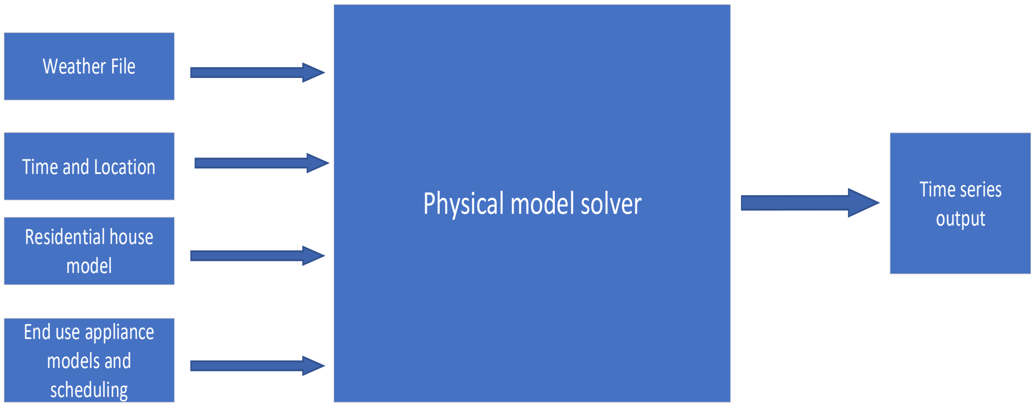

FIGURE 2.6: Architecture for building residential load models

From the Figure 2.7 below, displays the results for base case generated for summer season and it was observed that the peak occurs at 7.40pm and the demand during that time is 2215.85 kW. It is evident that the demand is low during the night as everyone is asleep as well as the HVAC load is low. During the base load period the demand stays constant near 800 kW. As the day begins and people start getting ready for their day, an increase in demand is observed. This demand continues to climb up as the outside air temperature increases and at the end of the day the demand reaches its peak, when people get engaged with the household chores such as cooking, washing clothes, watching TV etc. As the day is about to end, people stop their activities and also the outside air temperature reduces hence a plummet in load is observed.

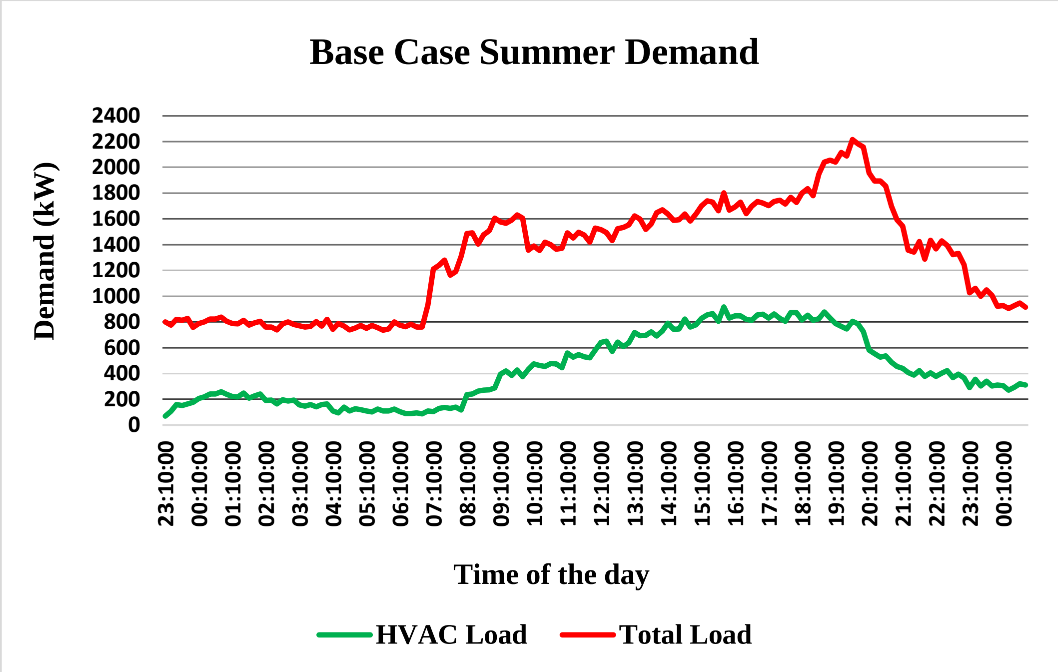

FIGURE 2.7: Demand profile for base summer case

Using this base case, various reference periods are defined, depending upon the loads, for application of various DR strategies.

i) Peak period – 5pm to 9pm

ii) Off peak period – 1am to 5am

Referring to section 1.1.2, the peaker and expensive plants would be dispatched from 5pm to 9pm and during the off-peak period only base load plants would be running. Hence, the most ideal period for peak shaving is the peak period and storing energy is the off-peak period.

2.5: Base Case Winter

Like the summer peak weekday case, a winter peak weekday case is developed. It is considered that the end use appliance usage will be like the summer season. The architecture used to obtain the time series output is similar as well. For a winter peak weekday case a day with lowest mean minimum temperature is chosen by observing the TMY weather file. The day with lowest mean minimum temperature will have maximum heating degree days (HDD).

Figure 2.8 represents the base profile for a winter peak weekday. As it can be observed that there are two peaks; one during the early morning and one during the late evening. The HVAC load is almost constant throughout the 24-hour period. There is slight decrease in the demand during mid-day hours as the temperature increases, and the heating requirement reduces. The two peaks are driven by the end-use appliances. The morning peak is when people wake up and start their activity and leave their homes. The evening peak occurs when people return home and finish their domestic chores. It is observed that, the system peak occurs at 7.40pm with a value of 1960 kW. During the off-peak period the demand stays fairly constant at 1300 kW.

Like the summer base case, reference periods are defined for the winter peak weekday case depending upon the loads.

i) Peak period – 7am to 10am and 6pm to 9pm.

ii) Off-peak period – 1am to 5am.

iii) Valley period – 12pm to 4pm.

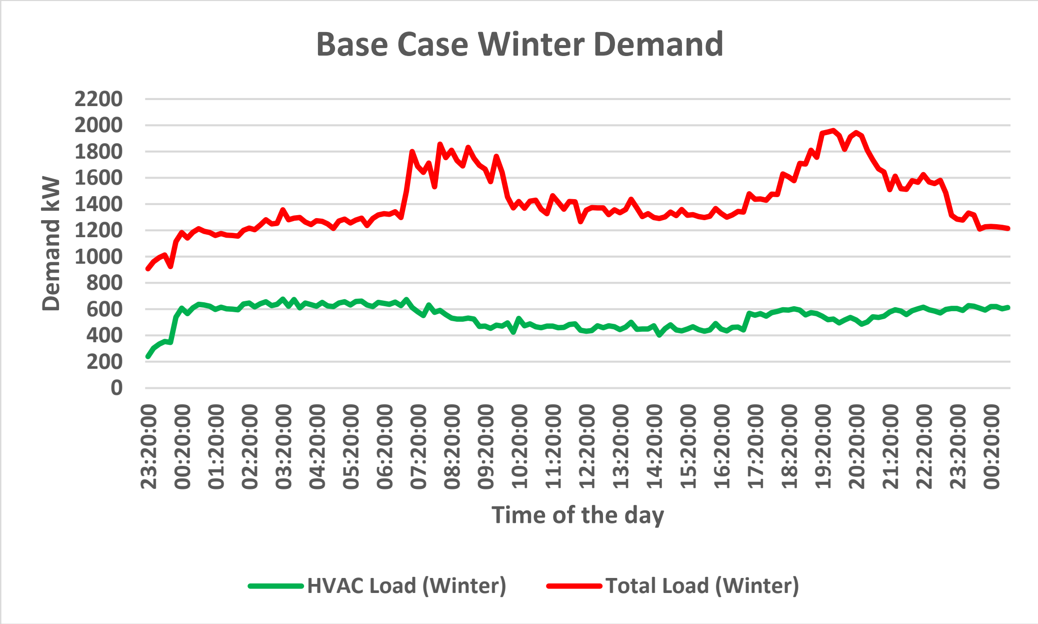

FIGURE 2.8: Base case winter demand

2.5: Summer Demand vs Winter Demand

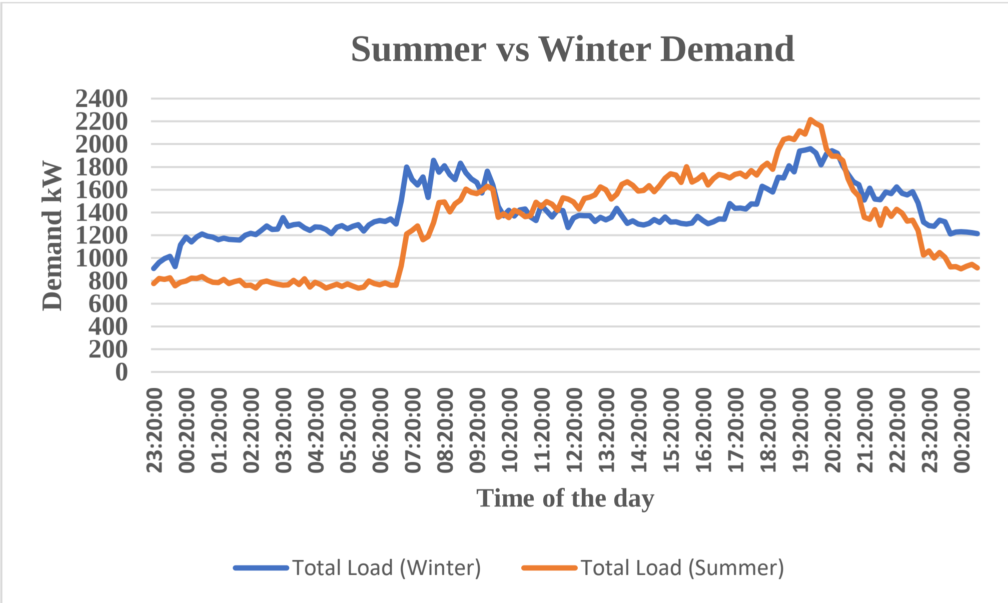

FIGURE 2.9: Summer Demand vs Winter Demand

From Figure 2.9 above shows the summer vs winter demand comparison it is evident that the absolute annual peak occurs during summer. Although the average demand is higher during the winter peak day. The HVAC load for both these cases is very different and there are various reasons for these results.

- For winter case the HVAC load is high during the night. The reason for HVAC load being high at night is due to the fact that, the night air temperature during this particular day was very low.
- For summer case the HVAC load is low during the night and most of the end-use appliances are not being used hence the total demand is very low. During night time the outside air temperature is moderate and the cooling demand for the HVACs is minimal.
- For winter case the HVAC load drops during the day as outside air temperature increases. For summer case this is exactly opposite. The cooling load increases during the day.
- The internal heat gains from appliances and people contribute to the heating load during winter reducing the heating demand. These gains work conversely during summer by adding to the cooling loads. Thus, during summer internal gains increase the cooling demand.
- Combination of high HVAC load, heat gains and end use appliances coincide with each other and hence, summer peak is greater than the winter peak.
- All the cooling equipment is electric whereas for heating the equipment used is partly electric and partly gas. This reduces the overall electric demand.
- Electric resistive heaters or bargeboard heaters are not centralized heaters; hence they would have to be modeled into multiple zones. Sufficient data on their sizing, saturation and usage in the South Atlantic region is not available.

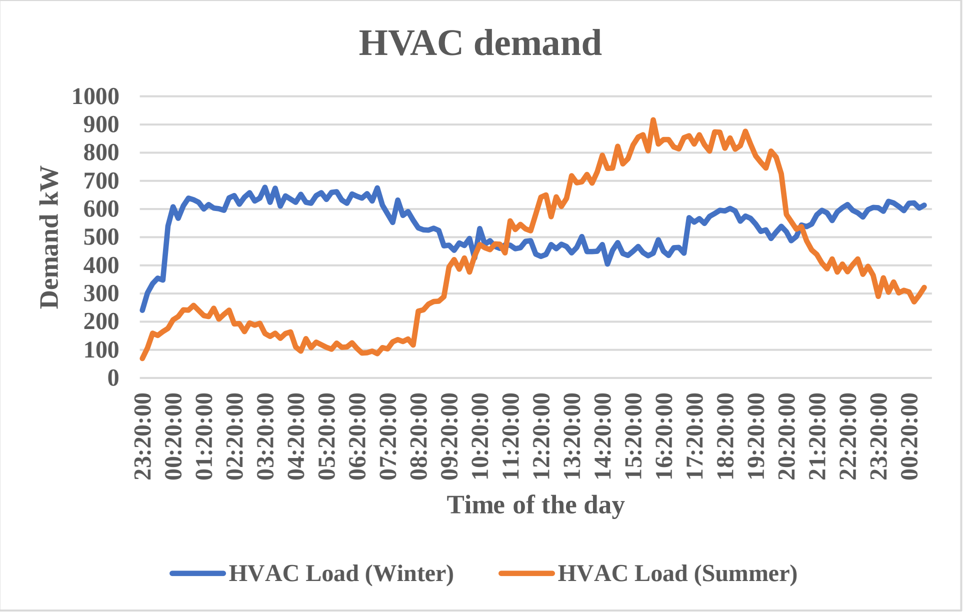

FIGURE 2.10: Summer cooling demand vs winter heating demand

As the absolute annual peak was observed during summer season, henceforth all the DR strategies applied will consider the summer case only. Although, for winter peaking cases similar strategies could be implemented without any major modifications.

CHAPTER 3: DR USING THERMOSTATICALLY CONTROLLED LOADS

After developing a base case, it is possible to predict the time period during which various DR strategies need to be implemented. From Figure 1.7, it is evident that thermostatically controlled loads such has HVACs and electric water heaters make up for the maximum demand in the residential buildings. Hence, reducing consumption from these loads should be the most effective strategy. Since the advent of smart grid technologies such as advanced metering infrastructure (AMI), programmable thermostats and remote access to these appliances through internet of things (IoT) it is possible for utilities to accurately determine the needs of customers and implement DR strategy accordingly.

Almost every utility has a DR program for its customers. The pioneer DR programs were based on direct load control or curtailment of these consumer loads. These TCLs are flexible loads and they can work in aggregation to provide the required capacity reduction. Apart from TCLs, it is possible to perform DR on other end-use devices as well, provided that they have the ability to communicate with the grid. A priority based approach for multiple device groups to participate in DR programs has been proposed in [39].

3.1: DR in HVACs

In direct load control programs for HVACs, it is essential to consider the duration of DR signal as longer duration signals could increase the indoor temperature significantly and create discomfort for the customers. This could create a negativity about the DR program and non-participation would rise. The DR strategy has been best implemented in study by Lawrence Berkeley National Laboratory study on evaluating customer impact on participating in the Southern California Edison’s DR program [40].

According to ASHRAE standard 55-2010, the cyclic variation should not be less than 15 minutes. Within a cycle of 15 mins, the operative temperature should not exceed by 2 deg F [41]. The limits on temperature variation for a particular time period is given below in Table 3.1. The DR strategies implemented in the next sections have adhered to these numbers. Studies have been performed to measure the DR obtained using air conditioners/ HVACs in [42, 43].

TABLE 3.1: ASHRAE standard 55-2010 indicating maximum operative temperature change

Time Period (hours)	0.25	0.5	1	2	4
Maximum Operative Temperature Change Allowed (Deg C)	1.1	1.7	2.2	2.8	3.3
Maximum Operative Temperature Change Allowed (Deg F)	2.0	3.0	4.0	5.0	6.0

3.2: DR in Electric Water Heaters

In residential buildings, electric water heaters have been identified as perfect candidates due to their ability to store energy in the form of thermal energy. Also, these EWHs contribute to a large amount of load, and they have very high-power ratings (usually 4.5kW). Also the power consumption is co-incident with the utility's peak demand [44, 45]. These water heaters are similar to HVACs, and a longer DR signal would cause a large decrease in the water temperature, which would eventually interfere with the customer's comfort. A simple peak shifting algorithm for water heaters is proposed in [46].

3.2.1: Water Temperature in EWH

The temperature for water heater set-point has been identified in various studies. A pre-set value of 125 Deg F is a typical set point for water heaters based on a study by

Lawerence Berkeley National Laboratory (LBNL) on hot water usage data in residential homes [47]. This is also beneficial from the perspective of consumer health. According to a 2003 report on Legionella bacteria, it was observed that the bacterial growth is optimum between temperatures 95 Deg F to 113 Deg F [47] and the range for growth is between 68 Deg F to 122 Deg F [47]. Hence, any temperature below 122 Deg F is not recommended.

3.3: HVAC vs Water Heaters

Amongst the two TCLs - the HVAC and the water heater, most of the studies select HVAC. Both these TCLs have a huge potential for providing DR support. Although, there are various fundamental differences between the operation of these two devices:

i) Specific heat capacity: HVACs are used for cooling/heating air, whereas water heaters are used for heating water. Air and water are two different substances, and both have a difference in their specific heat capacities. Specific heat capacity is defined as amount of energy required to change the temperature of the unit mass of a substance by one degree [48]. Specific heat capacity of water is 4.23 times greater than air [48]. Hence this indicates that the energy storing capacity of water is greater than air. Water heaters can be used to store energy for longer times as compared to HVACs.

ii) Operation: HVACs and water heaters operate continuously, although the energy consumption of water heaters is much less than the HVACs. The time intervals during which water heaters are not is use are large, whereas, HVACs cycle throughout the day to maintain the temperature around the set-point temperature.

iii) Loads: The amount of load on HVAC is much higher when compared with the water heaters. The volume of water to be heated is much less than the volume of air that needs to be cooled. The loads on HVACs are more predictable than water heaters, as the hot water consumption is solely based on human behavior.

3.4: DR Signal for TCLs

Using various load forecasting techniques, utilities have information about the duration of peak period and the demand during this peak period. Using the base from section 2.4 and 2.5 as a reference, we know that peak period during summer is usually between 5pm to 9pm, whereas, during winters it is between 6pm and 8pm. Controllers are used to adjust the demand from these TCLs. These controllers are installed on the TCLs of participating customers. From the reference demand curve, a target demand reduction is set. As described in section 1.1.2, usually a 15-20% peak reduction would avoid generation from peaker plants. Hence a 20% target reduction is selected. When the demand is within this range the controllers on these TCLs will react and try to ramp down the demand.

3.4.1: Controllers

Controllers are attached to each thermostatically controlled device. The utility will communicate with the TCLs using these controllers. Depending upon the type of utility, the type of signal will vary. For a market-based utility, the type of signal will be price-based signal, whereas a regulated utility will send out demand signals. Depending upon the level of the signal, the TCLs will react. These controllers are transactive controllers which are broadly referred to a type of market-based building control systems [49]. These transactive controllers are specifically designed to react to the thermostatic set points [50]. For a controller average price or average demand, the rolling standard deviation, current market price or current demand are used to determine the operational set points of the controller object [50].

3.4.2: Controller Operation for HVACs

In this study, passive controllers are used. These are like transactive controllers except that they don't have the capability to bid back into the market. This kind of controller is used since this can be implemented by both regulated utility as well as market. This type of controller is more suitable for TOU and CPP rates [50].

For cooling mode operation certain parameters can be set by the user which are described below:

i) Range high: This is the allowable temperature rise from the current cooling setpoint the participant is willing to allow before it becomes too hot.

ii) Range low: This is the allowable temperature decrease or pre-cooling from the current cooling setpoint the participant is willing to allow before the DR signal is sent.

Similarly, for heating mode operation the functionality of these parameters gets reversed as described below:

i) Range high: This is the allowable temperature increase or pre-heating from the current heating setpoint the participant is willing to allow before the DR signal is sent.

ii) Range low: This is the allowable temperature decrease from the current heating setpoint the participant is willing to allow before it becomes too cold.

Other important properties associated with the controller object are average price or average demand and the standard deviation. These quantities are decided by the utility.

In this study it is assumed that all the participants in a scenario are willing to participate in the DR program. Hence standard deviation is 1 as well as the ramp is 1. The new setpoints for cooling mode operation are given by equation 7 and equation 8 [50]:

$$Tset = Tdesired + (Cleared\ demand - Average\ demand) * \left(\frac{Range\ high}{Ramp\ high * Standard\ Deviation}\right) \quad (7)$$

$$Tset = Tdesired + \left(\frac{Range\ high}{Ramp\ high * Standard\ Deviation}\right) \quad (8)$$

In passive controllers, the controllers are not allowed to bid back hence the values of clearing demand and average demand are irrelevant. Therefore, equation 7 can be also written as equation 8. As seen from equation 8 the set-points will change when clearing demand is different than average demand. In an organized market instead of demand signal a price signal will be considered. For cooling mode operation, Tset becomes the new adjusted setpoint for the controller and when the temperature rises above this adjusted setpoint plus the thermostat deadband, cooling will restart. Similar operation will occur in the heating mode. When both these demands are equal the controller is inactive.

For heating mode operation, range high is replaced with the range low and ramp high is replaced with ramp low in equation 9 and equation10 [50]. The equations can be re-written as shown below:

$$Tset = Tdesired + (Cleared\ demand - Average\ demand) * \left(\frac{Range\ low}{Ramp\ low * Standard\ Deviation}\right) \quad (9)$$

$$Tset = Tdesired + \left(\frac{Range\ low}{Ramp\ low * Standard\ Deviation}\right) \quad (10)$$

A graphical representation of the above description for cooling mode of HVACs is provided in the Figure 3.1. If the participant sets a cooling set point of 72 Deg F during the period where the demand is less than the average demand the HVACs continue their normal operation, when the cleared demand goes above the average demand, setpoints are altered. In this case we can see that the new setpoints are 78 Deg F as the range high for cooling mode was set to 6.

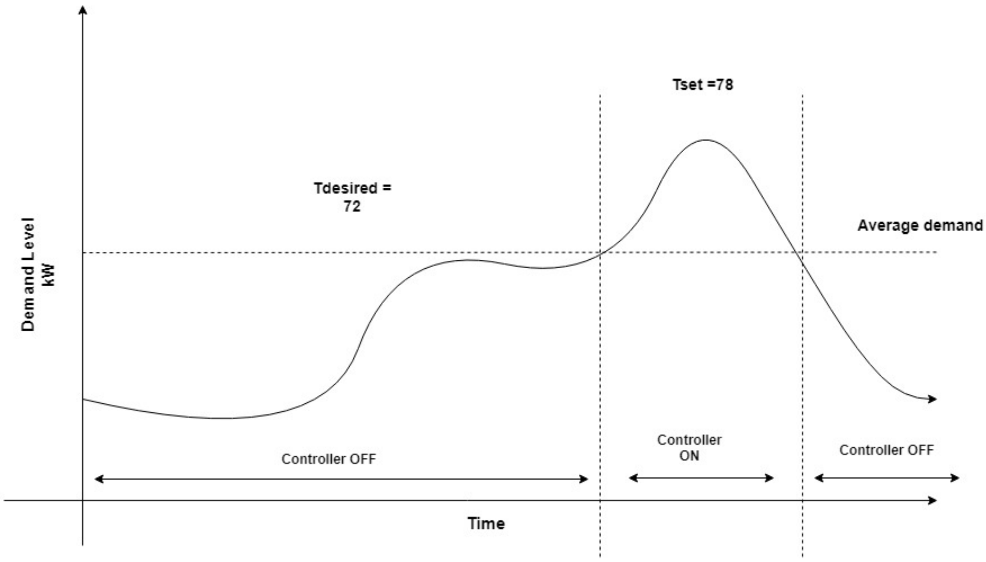

FIGURE 3.1: Graphical representation of cooling mode controller operation

3.4.3: Pre-cooling or Pre-heating

As explained earlier that for both cooling mode and heating mode of operations, participants can have a choice of pre-cooling or pre-heating respectively. During the night times when the load falls below a specific value, base load units must be ramped down. To avoid this consumer can use this pre-cooling or pre-heating.

In the cooling mode operation, instead of following the range high now, the controllers will follow the range low. This will be a negative number indicating the value of temperature the participant is willing to alter. The new setpoint Tset1 given is given by equation 11 and equation 12 [50].

$$Tset1 = Tdesired + (Cleared\ demand1 - Average\ demand1) * \left(\frac{Range\ low}{Ramp\ low * Standard\ Deviation}\right) \quad (11)$$

$$Tset1 = Tdesired + \left(\frac{Range\ low}{Ramp\ low * Standard\ Deviation}\right) \quad (12)$$

During the night-time when the cleared demand1 falls below the average demand1 the controllers will react by decreasing the setpoint to a new value. If the participant sets a cooling set point of 72 Deg F during the period where the demand is greater than the average demand1 the HVACs continue their normal operation, when the cleared demand1 goes below the average demand1, setpoints are altered. In this case we can see that the new setpoints are 70 Deg F as the range low for cooling mode was set to 2. A graphical representation for pre-cooling mode is as shown below.

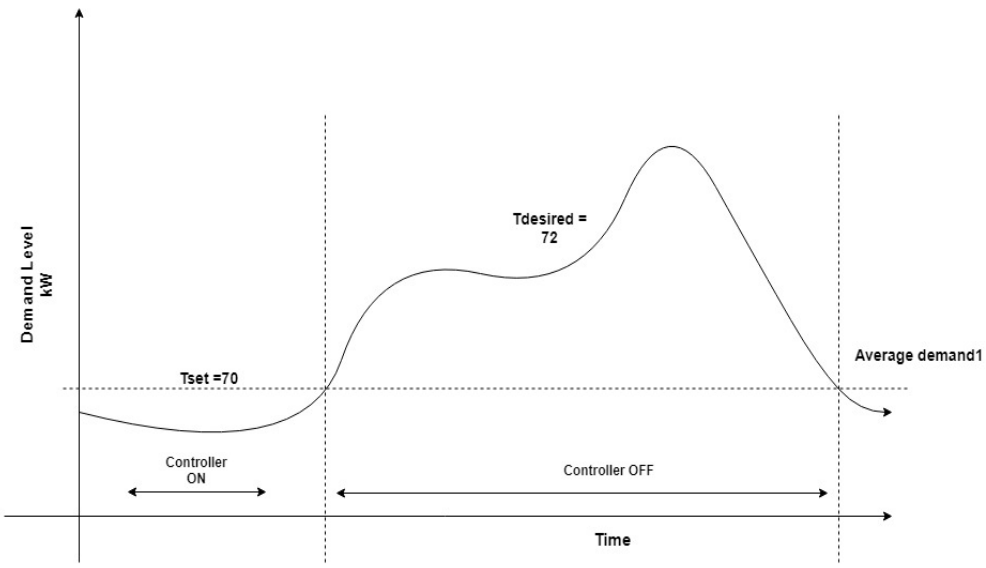

FIGURE 3.2: Graphical representation of pre-cooling mode

Combining pre-cooling mode with regular controller operation can be used for load-leveling. In load-leveling the HVACs will consume more power during low load level by shifting the setpoints to a lower value. During the peak periods, HVACs will turn down the consumption by shifting the setpoints to a higher value. When the cleared demand is between average demand and average demand1 the controllers remain inactive. The graphical representation for load-leveling will be as shown in Figure 3.3.

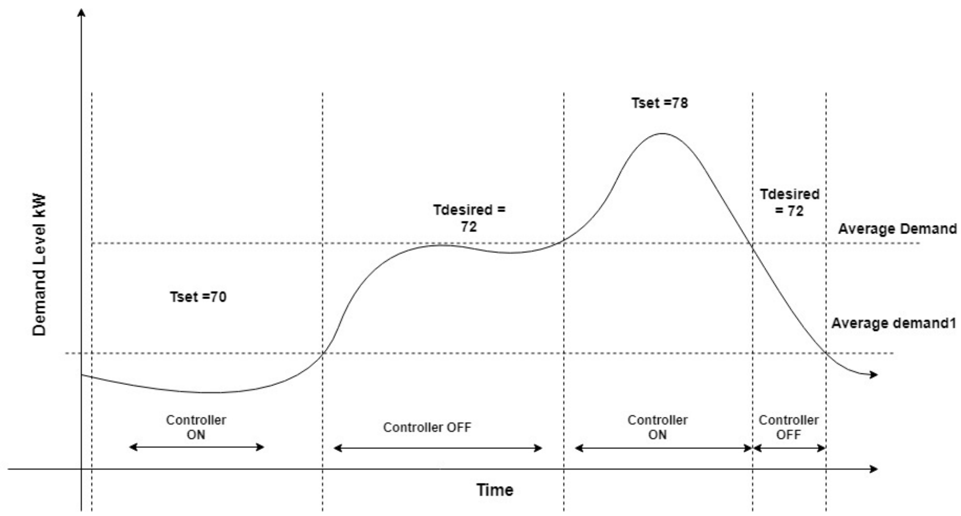

FIGURE 3.3: Cooling mode operation for load-leveling application

This operation will be similar in heating mode as well. The values for range low and ramp low will be replaced with range high and ramp high.

3.4.4: Controller Operation for Electric Water Heaters

The controller operation for electric water heaters will be exactly similar to heating mode operation in the HVACs. Both HVACs and EWH will be tested for various DR scenarios.

3.5: Customer Participation in DR Programs

DR programs require customers to reduce demand by shifting their consumption patterns. These DR programs may create some discomfort or deviation from regular behavior which could discourage the customers to participate in a DR program. Various studies have made an effort to estimate the number of participants in the DR programs [7, 51]. Apart from these reasons, lack of knowledge about a DR program will also create a decrease in the participation rate.

The number of participants is dependent on the participant rate and their eligibility in any DR program [52]. The number of eligible participants is based on various factors like the number of customers by a segment and the number of customers with specific equipment [52]. A FERC study has proposed a hierarchical architecture for participation in DR programs [52]. For this study various DR scenarios are created. It is assumed that all customers are eligible to participate in the DR program since, saturation of end-use appliances is already considered while creating the base model. The scenarios created are described in the Table 3.2.

TABLE 3.2: Number of participants in DR programs for TCLs

Scenario	No. of Participants		
	HVACs Cooling Mode	HVACs Heating Mode	Water Heaters
Base Case	0	0	0
25% Adoption	125	125	88
50% Adoption	250	250	178
75% Adoption	375	375	266
100% Adoption	500	500	355

For other appliances the same adoption cases will be considered if they are participating in the DR program.

3.6: DR potential of thermostatically controlled loads

3.6.1: Case Study

This is the simplest case where all the above-mentioned scenarios in Table 7. are simulated for analyzing the DR potential of TCLs. The demand reduction in each case is compared with the base scenario.

3.6.2: Unified DR Signal

Figure 3.4 displays the peak shaving potential of TCLs for summer peak weekday profile. Here, a 0% participation indicates the base case without any DR. Both

HVACs and EWHs are given a unified signal to reduce their demand at 19.00. From figure 3.4 it can be observed that the TCLs respond immediately. The HVACs setback (range high) their temperature by 6 Deg F whereas water heaters setback their temperatures by 20 Deg F. The DR signal stops at 21:00 and it can be observed that all TCLs come online at the same exact time. This causes a sudden need for demand among all the appliances. This effect is called as rebound effect from DR. It can be observed that, the peaks due to the rebound at 21:30 are much larger than the original system peak. Hence, instead of mitigating the peaks, DR will have adverse effects if a proper control on the devices is not implemented. Figure 3.4 and Figure 3.5 show the impacts of rebound when unified signal is used for DR.

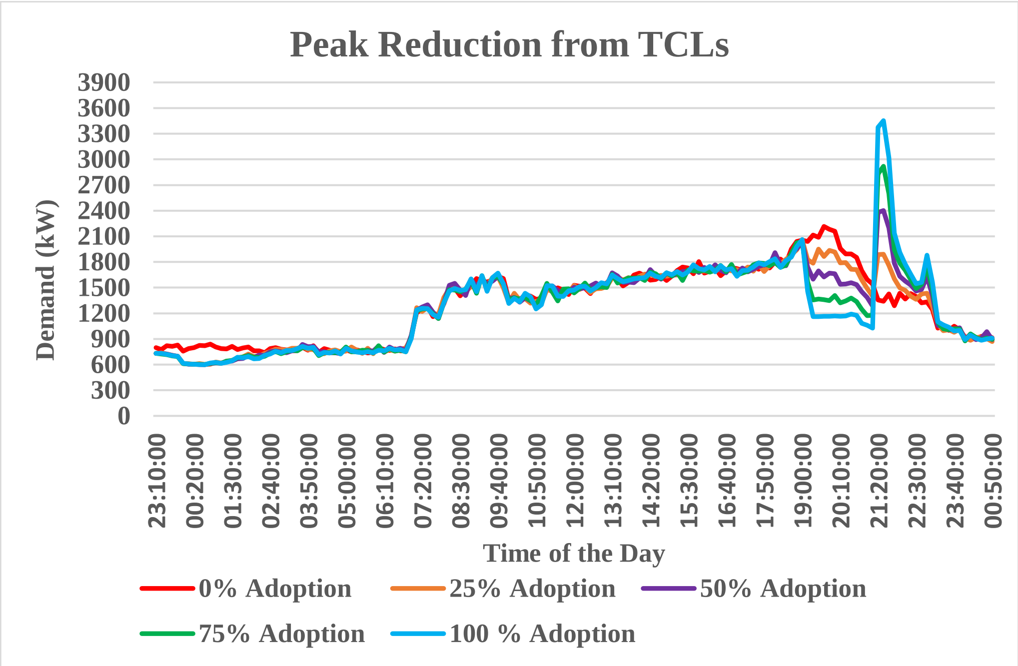

FIGURE 3.4: Peak reduction using TCLs

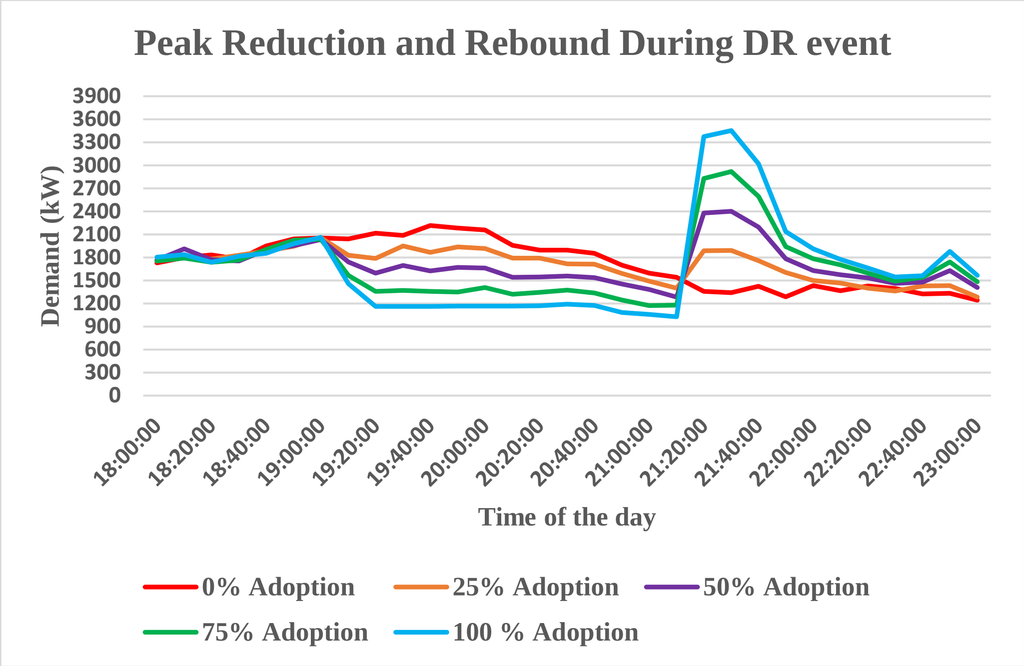

FIGURE 3.5: Peak reduction and rebound during the DR event

Table 3.3 provides a summary for the peak reduction using both TCLs.

TABLE 3.3: Summary of peak reduction for DR using TCLs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	350.93	15.8	325.25	14.67
50% adoption	589.36	26.6	-185.48	-8.3
75% adoption	856.54	38.6	-703.39	-31.74
100% adoption	1052.53	47.5	-1237.07	-55.82

From Table 3.3, it is clear that the rebound, instead of reducing the peak shifts the peak to a different time which is much larger than the original peak. For 25% adoption scenario rebound does not create much difference as the number of appliances responding to the DR signal is very small. It can be concluded that although the peak reduction without considering rebound increases as the adoption rate increases, the rebound effect creates larger system peaks which have adverse effects and these peaks increase as the adoption rate among the customers increases. For 100% adoption rate, the rebound is 56% greater than the original system peak.

3.6.3: Diversified Signal

Various techniques have shown that this rebound effect can be mitigated. The fundamental cause behind this rebound is all devices trying to recover after the DR signal and which causes them to come back online at the same exact time. Hence, if a diversity in signal is created, then devices can be brought back online in groups with a specific time delay between two groups.

In this study, for the purpose of proving that the diversity in signals would mitigate the rebound effect, 5 different signals are created. These 5 signals are applied to HVACs, and a similar set of 5 signals is applied to water heaters. There is a 20 min delay between each signal. Table 3.4 shows the duration, start time and end time for signals.

TABLE 3.4: Diversity amongst DR signals

Signal Name	Duration	Start Time	End Time
Signal 1	2 hours	19:00	21:00
Signal 2	2 hours 20 mins	19:00	21:20
Signal 3	2 hours 40 mins	19:00	21:40
Signal 4	2 hours	18:40	20:40
Signal 5	2 hours	18:20	20:20

Figure 3.6 and Figure 3.7 shows the mitigation in the rebound when diverse signals are applied to the system.

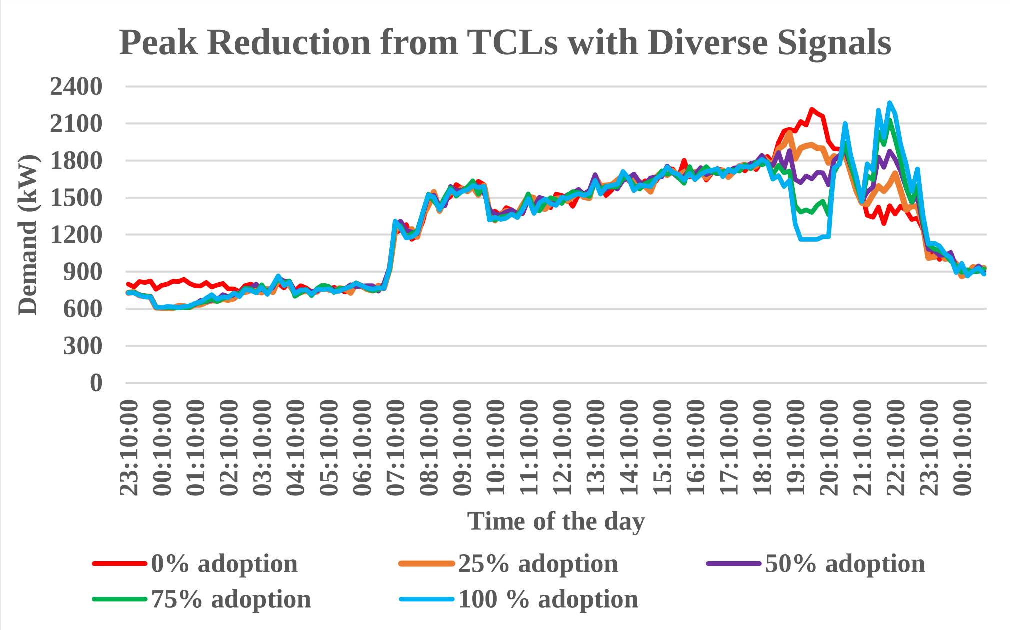

FIGURE 3.6: Rebound mitigation using diverse signals

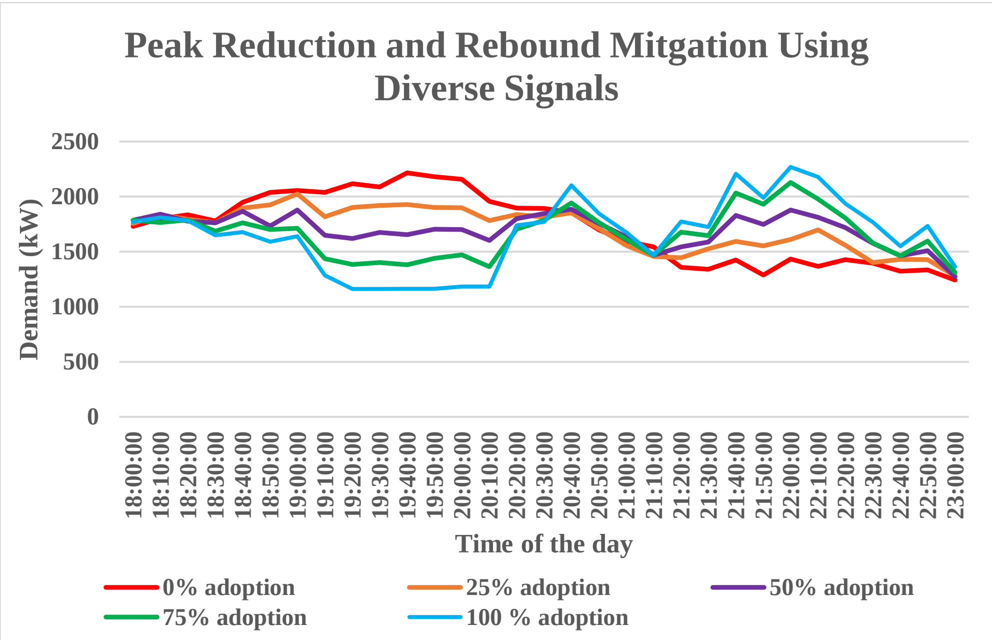

FIGURE 3.7: Peak reduction and rebound mitigation during the DR event

Table 3.5 provides a summary for the peak reduction and rebound mitigation by applying diverse signals to both TCLs.

TABLE 3.5: Summary of diversified signal in both TCLs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	288.61	13.02	288.61	13.02
50% adoption	562.64	25.39	337.95	15.25
75% adoption	834.44	37.65	87.28	3.9
100% adoption	1053.24	47.53	-53.12	-2.3%

Thus, from Table 3.5, it can be observed that the peak reduction increases when adoption increases. Also, the rebound is mitigated when compared with the values from Table 3.4 which indicates the scenarios for unified signal. Figure 3.8 shows a comparison between unified and diversified signal for 75% adoption case. It can be clearly seen that; unified signal creates massive rebound. Also, it can be concluded that the maximum potential for peak reduction using both TCLs is 47.5%.

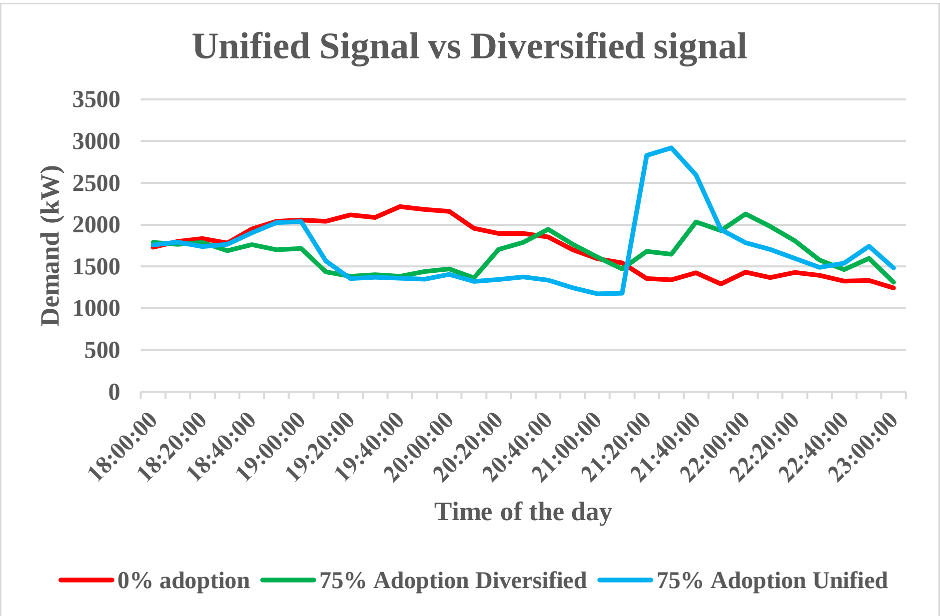

FIGURE 3.8: Unified signal vs Diversified Signal

The rebound can be further reduced by creating more diversity in the DR signals. This can be achieved by either one or all the measures mentioned below:

- Creating more signals
- Increasing the delay between the signals
- Varying the start and end time
- Spreading out the signals by increasing the duration of some of the signals

3.7: DR Using HVACs

In this section the potential of DR from air conditioner has been gauged. It is considered that participants in each adoption scenario shift their thermostat set-points by 6 deg F. The water heaters continue to work normally, and the DR signal is applied to the HVACs only. Figure 3.9 shows response from HVACs upon triggering a unified DR signal.

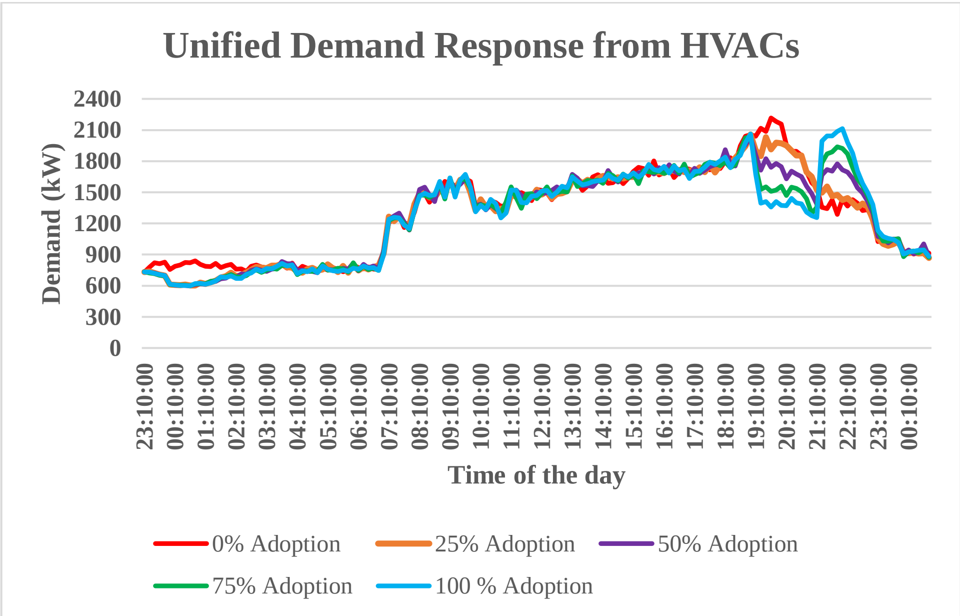

FIGURE 3.9: Unified signal for DR from HVACs

The above Figure 3.9 is for the whole day. Figure 3.10 indicates the peak reduction and rebound during the event horizon.

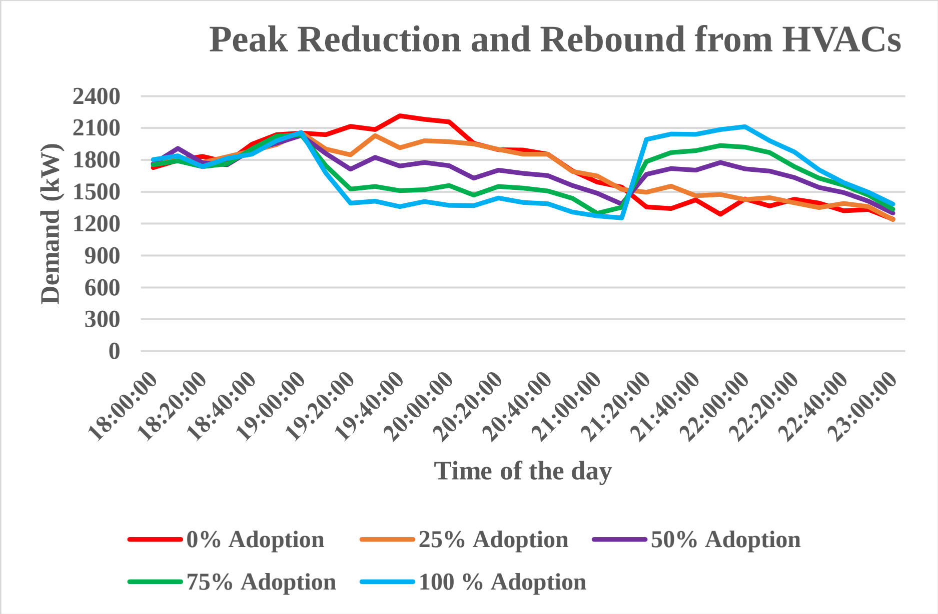

FIGURE 3.10: Peak reduction and Rebound from HVACs

The Summary of DR and rebound from unified signals is given in Table 3.6 below.

TABLE 3.6: Summary of unified signal in HVACs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	302.01	13.62	302.01	13.62
50% adoption	473.71	21.37	440.68	19.88
75% adoption	705.11	31.82	279	12.59
100% adoption	856.37	38.64	102.63	4.63

From Table 3.6, it is evident that for DR using HVAC only, increase in the adoption in DR programs by customers increases the peak reduction, although the rebound increases as well. In the HVAC only case, the rebound peak was less than the original peak despite triggering them with a unified signal. The peak reduction with rebound is highest for 50% adoption case.

3.7.1: Diverse Signals

Like the case for DR in both TCLs described in section 3.6.3, a diversified signal will be created to mitigate this rebound. A total of 5 signals are created for HVACs, while the water heaters continue their normal function. Figure 3.11 shows how the diversified signal helps in reducing the rebound.

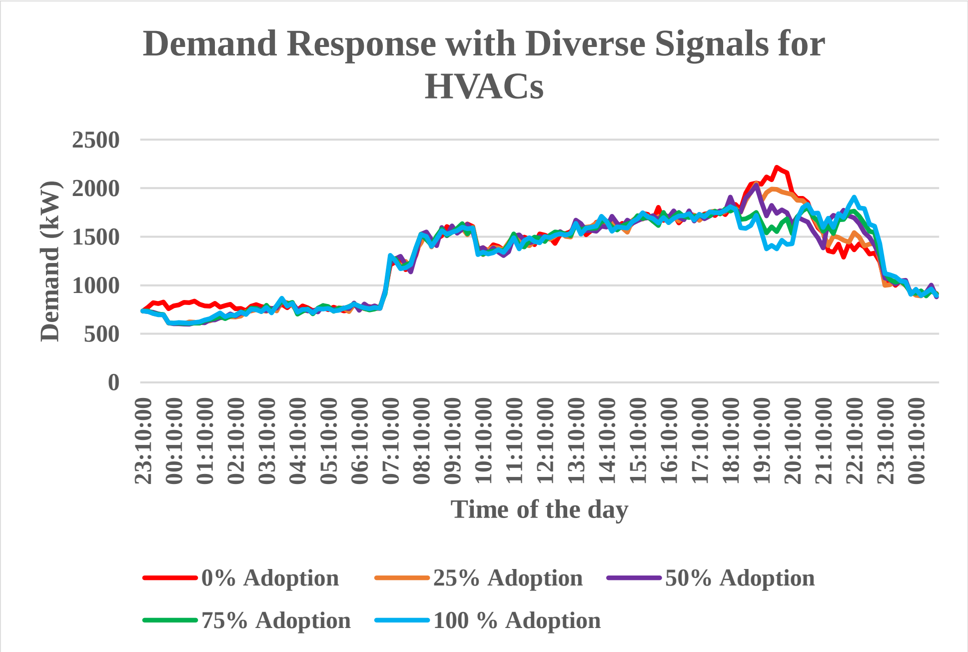

FIGURE 3.11: Diversified signal for DR from HVACs

Figure 3.12 shows the peak reduction and rebound mitigation for the DR event horizon only.

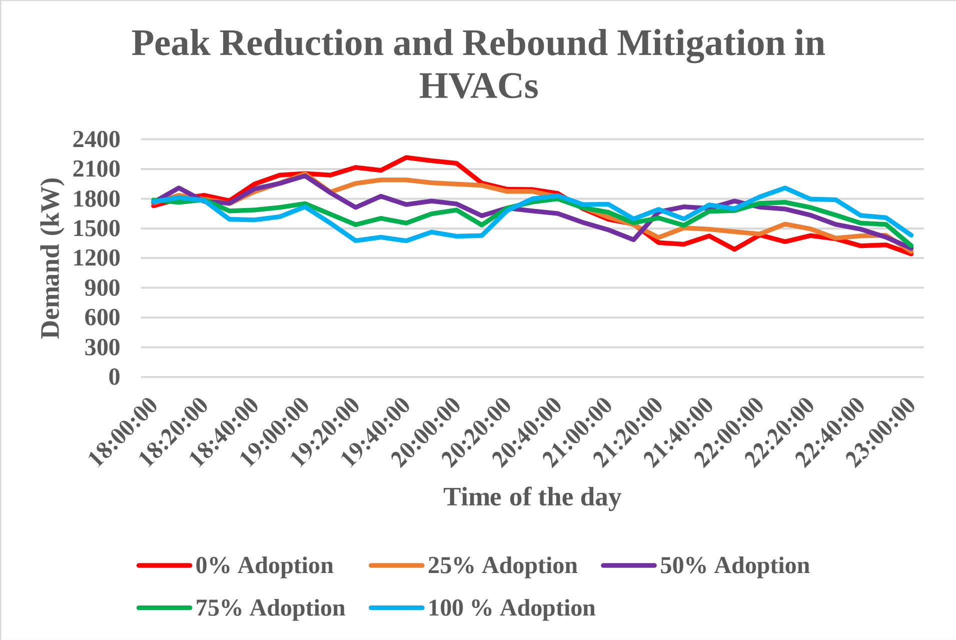

FIGURE 3.12: Peak reduction and rebound mitigation from HVACs

The summary for peak reduction and rebounds mitigation from HVACs is provided in Table 3.7.

TABLE 3.7: Rebound reduction due to diversified signals for HVACs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	226.41	10.21	226.41	10.21
50% adoption	473.71	21.37	440.68	19.88
75% adoption	662.54	29.90	453.49	20.50
100% adoption	841	37.95	102.63	13.87

Thus, from Table 3.7, it is evident that the rebound has fairly decreased when diversified signal is given instead of a single signal. The peak reduction without rebound is highest for the 75% adoption case at 20.5%. Thus, it can be concluded that the maximum potential of peak reduction by using HVACs is 38.64%. Figure 3.13 below shows rebound reduction when diversified signal is given.

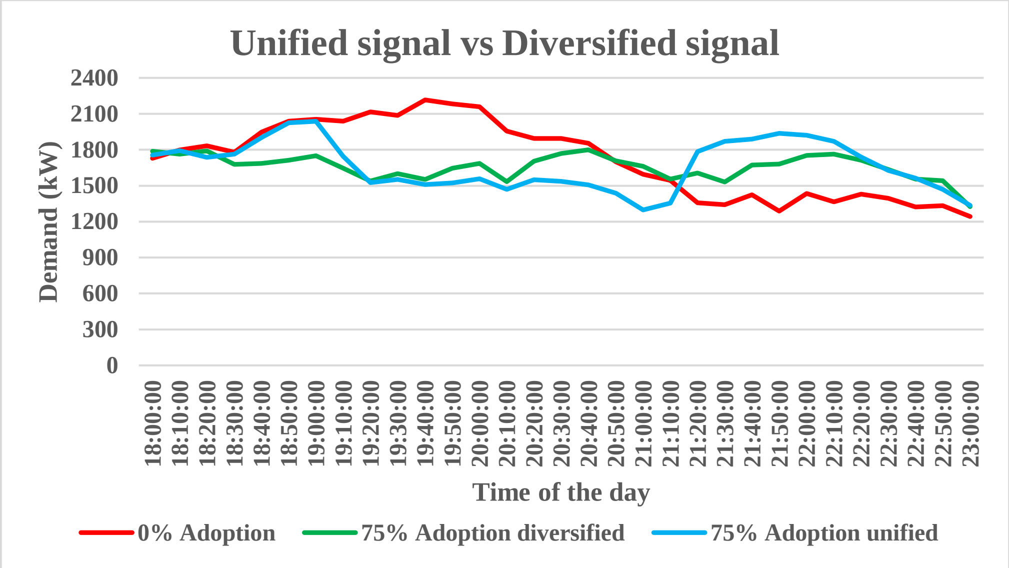

FIGURE 3.13: Unified vs Diversified signal for HVACs

3.8: Impact of Thermostat Range on DR

The thermostat range here is the temperature range by which the participants are willing to roll back their thermostats from their original setpoints. The original case had a 6 deg F temperature range. To study the impact, a case where all HVACs have a 2 deg F range is created. Figure 3.14 shows the impact.

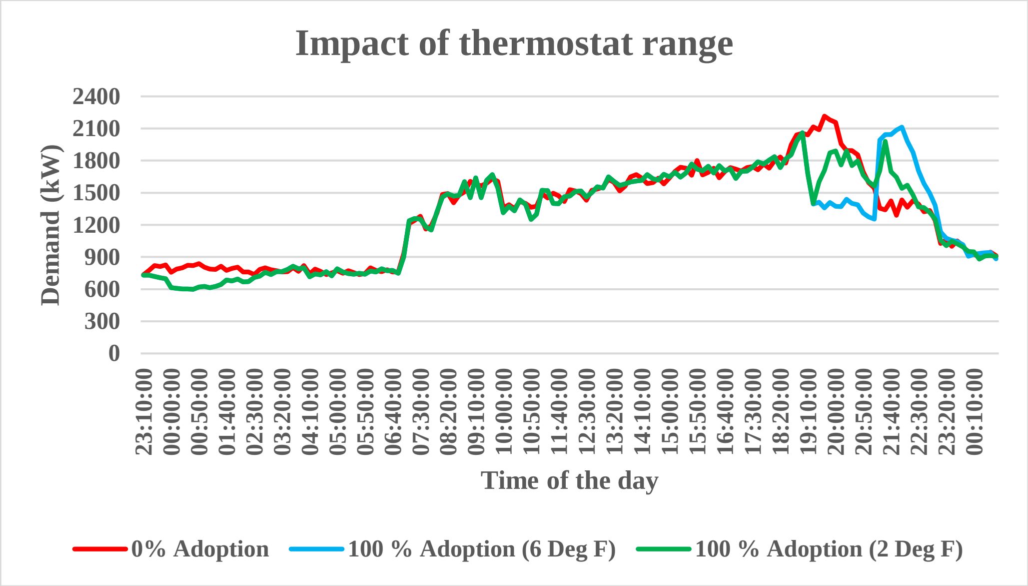

FIGURE 3.14: Impact of thermostat range

Figure 3.15 shows the impact during the DR event duration. The most significant impact is on the DR duration. For a 2 Deg F program, the DR duration is around 20 mins only whereas for the 6 Deg F program, the maximum reduction achieved remains for the entire 2 hours DR duration. The temperature inside the participating houses starts to rise when the thermostats are set back, a 2-degree gain will be completed quickly but, since the house has some thermal resistance it will take a long time to gain that 6-degree range.

It can be concluded that for achieving a longer DR capacity reduction, a higher temperature range should be set, although the drawback of selecting a higher temperature range will see larger rebounds in the system as can be observed from Figure 3.15.

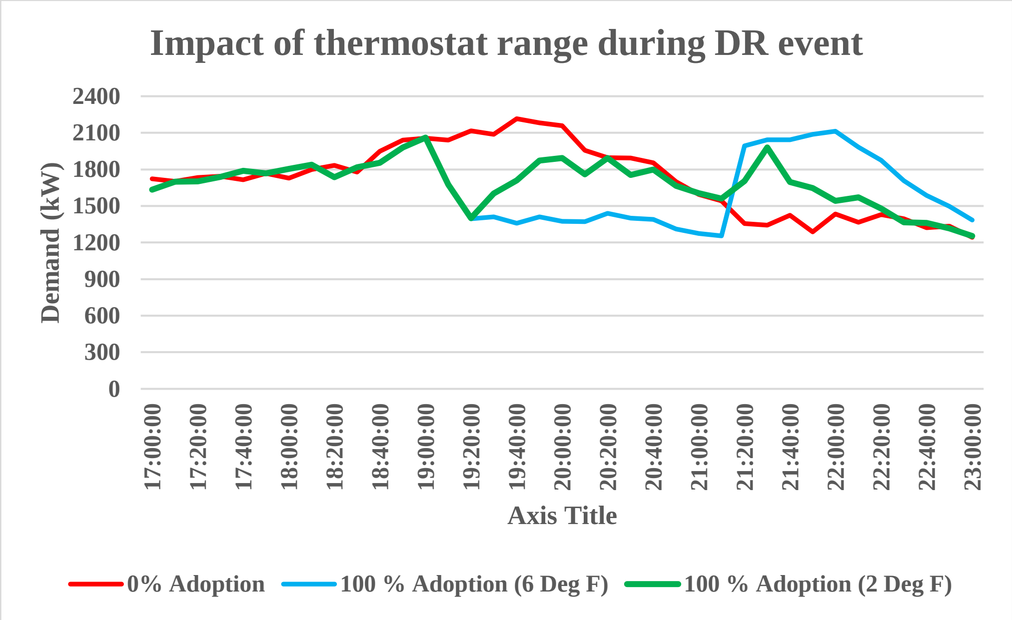

FIGURE 3.15: Impact of range during the DR event

3.9: Demand Response from Water Heaters

In this section potential of DR from electric water heaters has been studied. Electric water heaters are slightly different from HVACs in terms of their operation although, both are thermostatically controlled flexible loads. In the initial assessment for DR, the water heaters are completely shut during the DR duration. In the next cases, the heat storage capacity of the water heaters has been examined. Figure 3.16 depicts the DR from electric water heaters when a single unified signal is triggered during the DR event. From Figure 3.16 it is evident that a unified signal in water heaters will produce a rebound similar to HVACs.

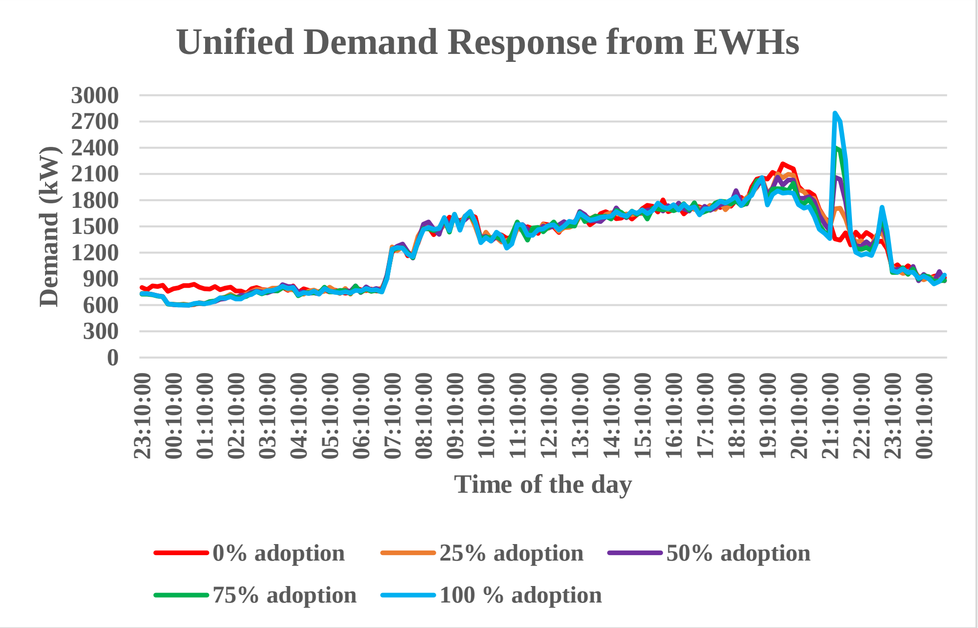

FIGURE 3.16: Unified DR from the water heaters

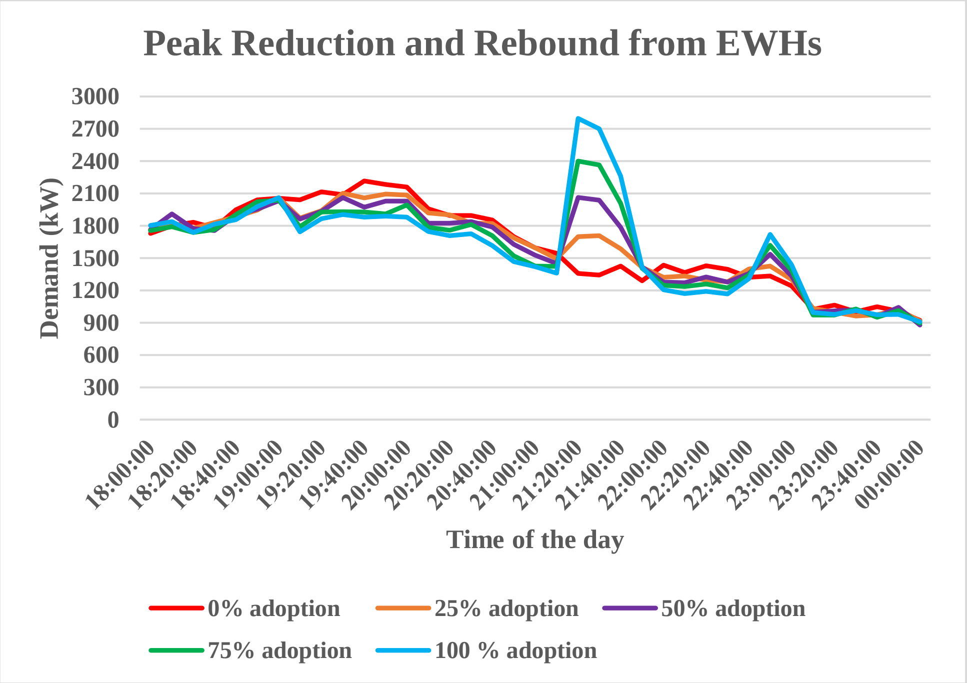

FIGURE 3.17: Peak reduction and rebound from water heaters

Table 3.8 provides a summary for unified DR from electric water heaters.

TABLE 3.8: Summary of unified signal in EWHs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	158.35	7.1	158.35	7.1
50% adoption	244.92	11.05	153.26	6.9
75% adoption	286.76	12.94	-184.62	-8.3
100% adoption	335.39	15.13	-580.86	-26.2

From the above Table 3.8, it is evident that unified signal produces a massive rebound in EWHs. The rebound produced is very high as the power rating of each EWH is approximately 4.5 kW. A peak 26.2% higher than the original peak is observed when 100% participant react to the unified signal. The maximum potential without rebound is 15.13% for 100% adoption case, which is much less than 38.6% obtained from the HVACs. This difference arises due to the operating characteristics of both these devices.

3.8.1: Diversified Signal

Similar to the case for DR in both TCLs described in section 3.6.3, a diversified signal will be created to mitigate this rebound. A total of 5 signals are created for EWHs while the HVACs continue their normal function. Figure 35 shows how the diversified signal helps in reducing the rebound.

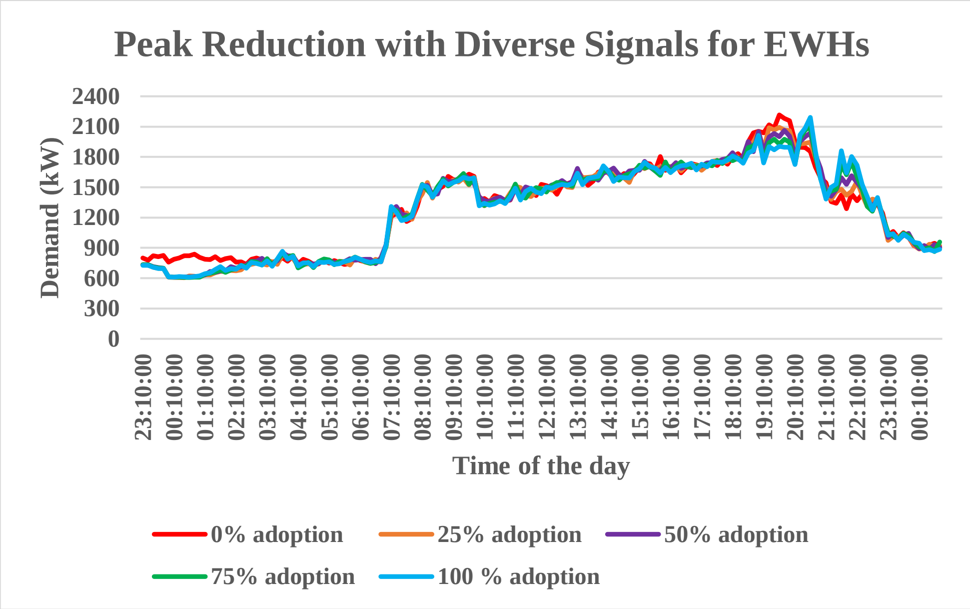

FIGURE 3.18: Peak reduction with diverse signals for EWHs

Figure 3.19 shows the peak reduction and rebound mitigation for the DR event horizon only.

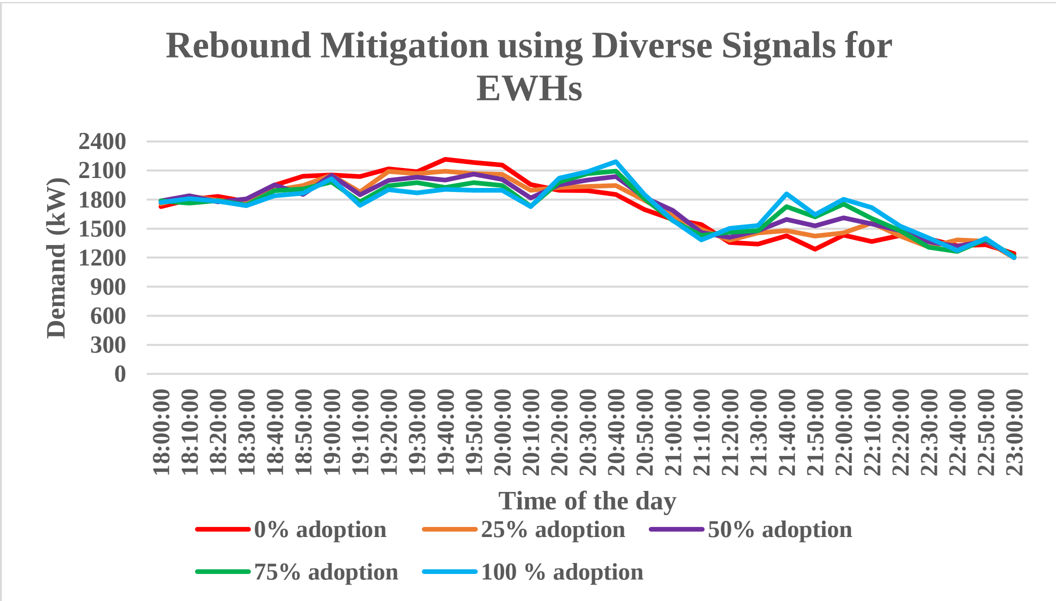

FIGURE 3.19: Rebound mitigation using diverse signals

Table 3.9 provides a summary for rebound mitigation using diverse signals in EWHs.

TABLE 3.9: Summary of diverse signal in EWHs

Adoption Scenario	Peak reduction without rebound kW	% Peak reduction without rebound	Peak reduction with rebound kW	% Peak reduction with rebound
0% adoption	-	-	-	-
25% adoption	123.14	5.55	123.14	5.51
50% adoption	215.38	9.72	176.70	7.97
75% adoption	288.82	13.03	121.96	5.50
100% adoption	311.54	14.05	24.35	1.09

From the above Table 3.9, it is evident that the diverse signal reduces the rebound in the electric water heaters. The peaks tend to reduce for every adoption scenario unlike the unified signal, but maximum potential with rebound is obtained for 50% adoption case at 7.97%. Figure 3.20 shows the difference between the unified and the diversified signals for the EWHs. The rebound which occurs during the unified case is well above the original system peak, whereas in the diversified scenario, it is below the original system peak.

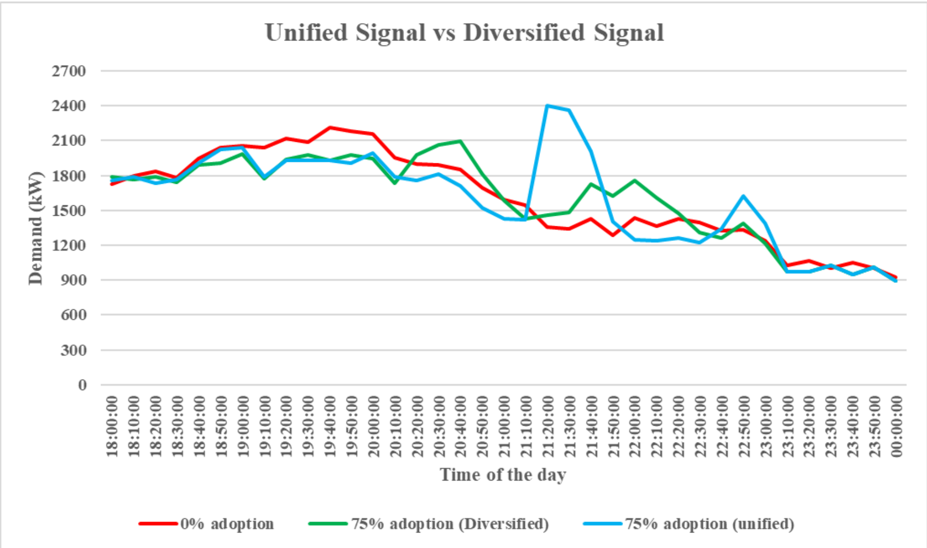

FIGURE 3.20: Unified vs diversified signals for EWHs

3.9: EWH vs HVAC Demand Response

In the above sections, the potential of two thermostatically controlled devices - water heaters and HVACs, has been analyzed in 3.7 and 3.8. There are clear differences between the two devices due to their operating characteristics and physical properties as described in section 3.3.

The main observations from the analysis are:

i) HVACs have more DR capacity than water heaters. The primary reason for this is, HVACs operate more frequently than water heaters.

ii) HVACs have a shorter DR duration as compared to EWHs, as the water has a very high specific heat capacity.

iii) Due to the high rated power of water heaters, the rebound from water heaters is higher than the one from the HVACs.

3.10: Using Energy Storage for Load Leveling and Mitigating Rebound Effects

Use of energy storage for peak shaving has been reviewed in several studies. With the decreasing prices, energy storage is becoming a lucrative option for providing services like peak shaving and other ancillary services for the utility [53]. As observed in the previous section 3.6 thermostatically controlled loads create a rebound when they are used for DR. Energy storage can be used to mitigate these rebounds created by TCLs as well. There are several types of energy storage systems, but this study will focus on battery energy storage system using lithium ion batteries. Lithium ion contributes to more than 80% of the installed capacity battery storage in operation in the United States [53]. The high energy density, high-cycle efficiency and fast response makes them the perfect choice for residential purposes. Other storage options like compressed air storage systems or flywheels have better performance, but for this application BESS is a better fit, due to its low initial costs and less site requirements [54, 55].

In this study, battery energy storage system (BESS) will be primarily used for load leveling and mitigating the rebound effects created by the TCLs. A simple yet effective approach for peak load shaving using BESS by maintaining the SOC has been discussed in [54].

3.10.1: BESS Operation for Load Leveling

In this study, BESS are considered to be distributed at the customer location. The primary objective of these BESS is to mitigate the rebound effects and level the load. Hence, their operation schedule is based according to the DR events. Energy storage is charged during the night time or during the afternoon valley period when the demand is very low, and the prices of electricity are low as well. This stored energy is then discharged during the peak period. Referring to the base case scenario in section 3 it can be observed that, for summer case peak period is defined from 5pm to 9pm whereas off-peak period is defined from 1am to 5am. Hence these periods will be used for discharging and charging the energy storage. Figure 3.21 describes the algorithm for battery operation.

As the battery charging and discharging is based on the peak and off-peak periods, the base demand profile is provided as an input for the battery controllers this demand profile is a time-series profile. For discharging, the DR event signal is fed as input as well. When the DR event occurs, the batteries start discharging and they keep discharging until 1 hour after the DR event. As the TCLs start their recovery, there is a risk of rebound, hence during this period the discharging batteries will provide the support. Thus, the discharge of batteries will help mitigate the rebound. If there is no

DR event the controller checks if the current time is between 1am and 5am which is the charging period. If not, then the battery remains inoperative.

The battery charging rates, discharging rates and other factors which will impact the load leveling and rebound mitigation performance will be discussed in the next section.

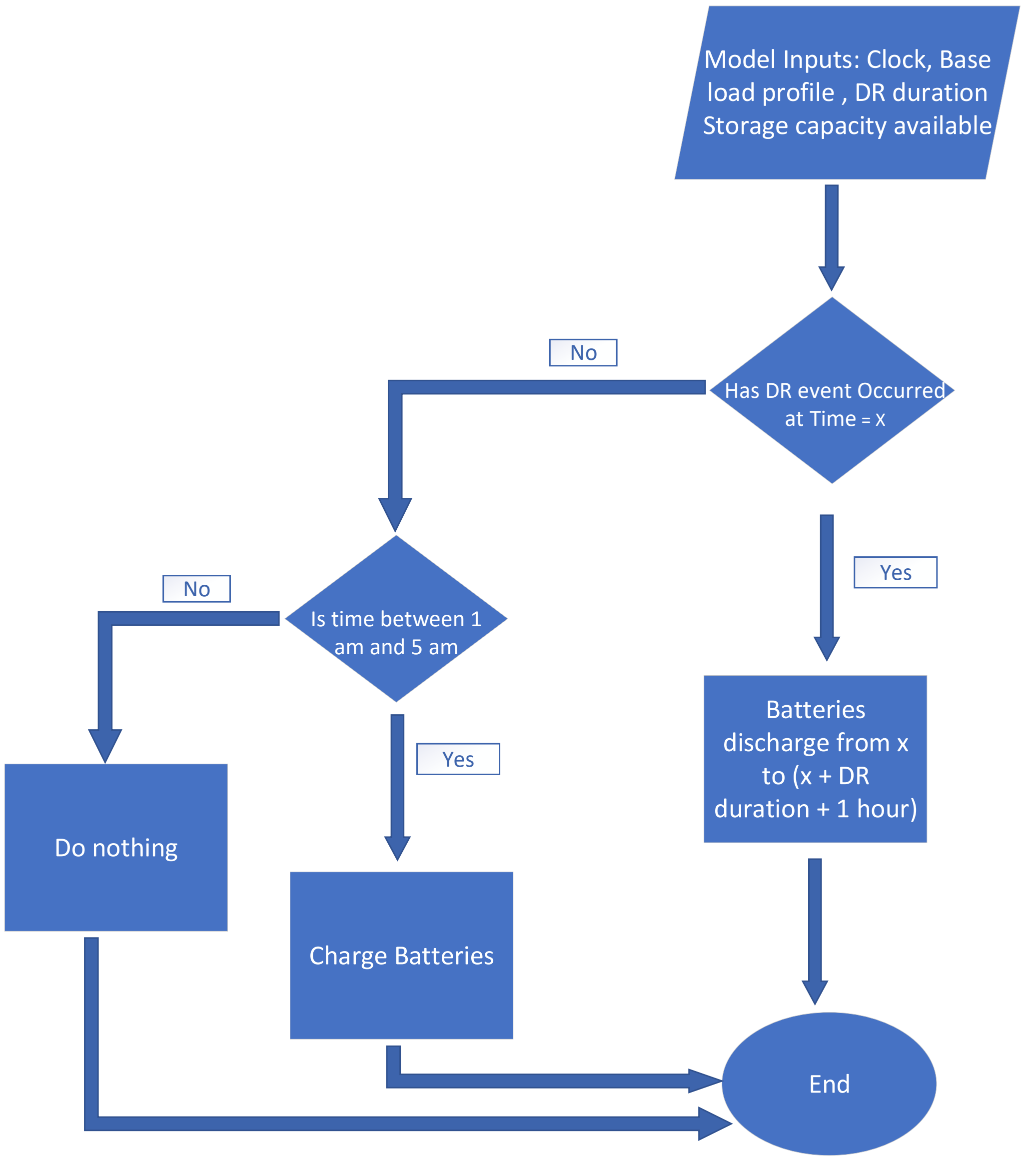

FIGURE 3.21: Battery scheduling algorithm for load leveling and DR mitigation

3.10.2: Battery Model

In this study as mentioned in above section 3.10, lithium ion batteries are being used due to their characteristics as well as commercial availability. The Tesla Powerwall, developed for implementation in residential houses, has been modeled [56]. The capabilities such as self-solar consumption and time-based control make it an attractive option [56]. Table 3.10 describes the characteristics of BESS used in modeling.

TABLE 3.10: Battery model description

Battery Characteristic	Value
Usable Capacity	13.5 kWh
Efficiency	90%
Power	5kW continuous
Maximum Charging rate	5kW
Maximum Discharging rate	5kW
Depth of Discharge	100%
Initial SOC	0.0
Round trip efficiency	90%

3.10.3: BESS for Load Leveling and DR Rebound Mitigation

As explained in section 3.10.1, the battery energy storage system's potential for DR and rebound mitigation were tested. Two cases are developed as described in Table 3.11. Figure 39 below shows rebound mitigation using BESS for 25% adoption scenario.

TABLE 3.11: Energy storage scenarios

Scenario		
Case 1	25% DR participation	25% BESS adoption
Case 2	100% DR Participation	25% BESS adoption

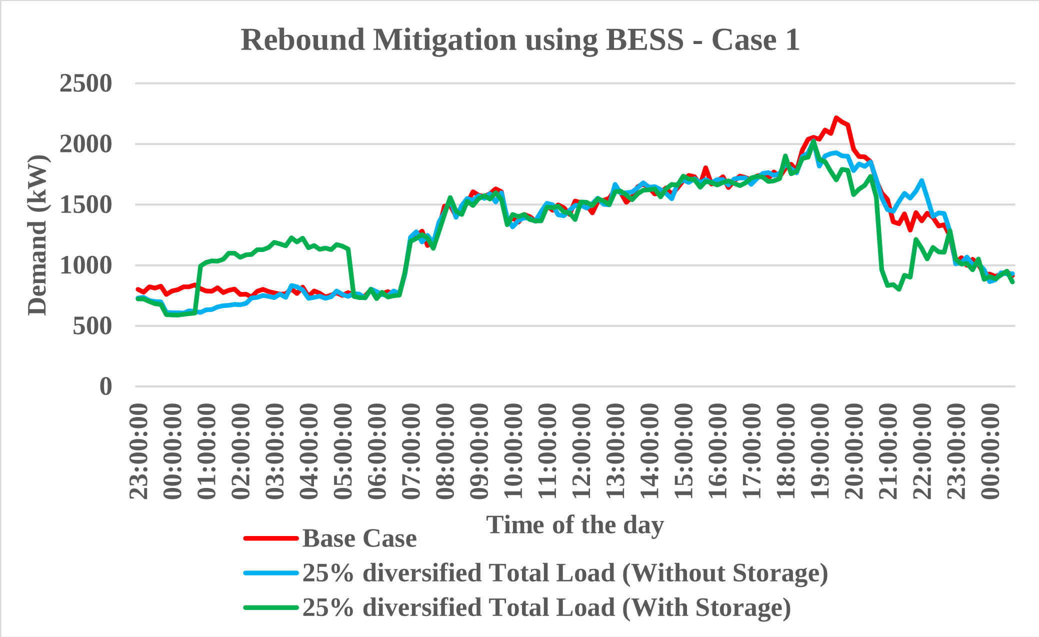

FIGURE 3.22: Rebound mitigation and load leveling for 25% DR and 25% BESS adoption scenario

Figure 3.22 shows how BESS can be used for reducing the rebound caused by DR. Also, during the off-peak period it is evident that charging of the batteries increases the demand which can support the load leveling function. Similarly Figure 3.23 represents case 2 for BESS.

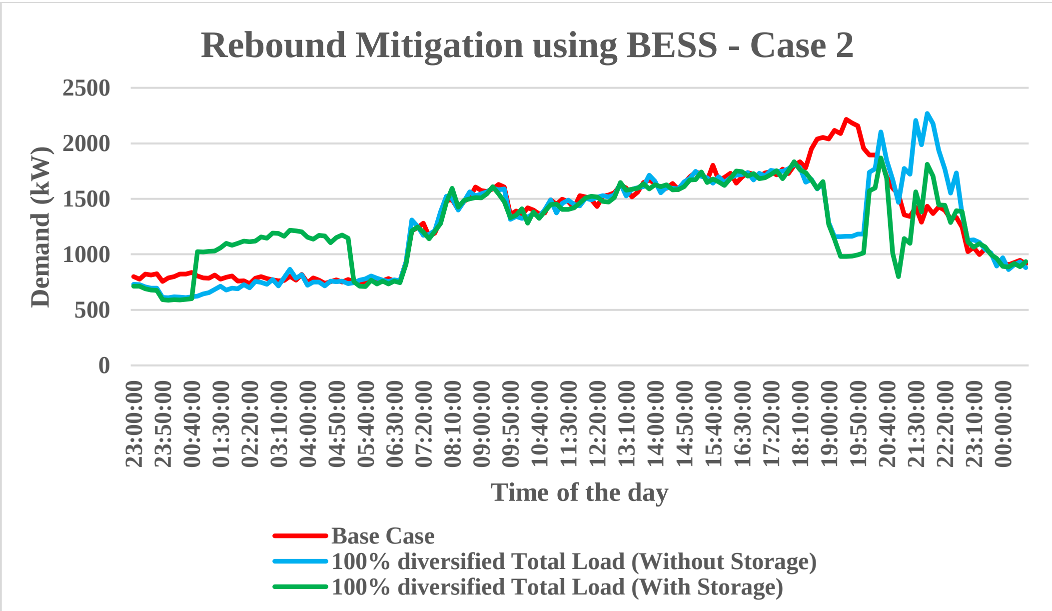

FIGURE 3.23: Rebound mitigation and load leveling for 100% DR and 25% BESS adoption scenario

From the above Figure 3.23, it is evident that the rebound has decreased massively, even with just 25% participants adopting the BESS. Table 3.12 provides a summary for with and without battery energy storage scenarios.

TABLE 3.12: Battery storage and no battery storage comparison

Scenario	Peak reduction without rebound (kW)	% decrease in peak with respect to base case	Peak reduction with rebound (kW)	% decrease in peak with respect to base case
Base case	0	0	0	0
Case-1 without storage	288.65	13%	288.65	13%
Case-1 with Storage	425.98	19.2%	425.98	19.2%
Case-2 without storage	1053.57	47.54%	-53.08	-2.3%
Case-2 with storage	1233.48	55.66%	509.10	23%

The above Table 3.12 indicates the importance of BESS in reducing the peaks as well as mitigating the rebounds. For case 1, where 25% DR participants are involved the rebounds are minimum hence the mitigation is not clearly observed. The peak reduction improves from 13% to 19.2% when BESS are installed. For case 2, 100% DR participants create a rebound which creates peak-shifting. The peak demand with rebound is 2.3% higher than the original demand. Although, with BESS this rebound is reduced significantly and the new peak demand is 15.7% less than the original demand.

Battery energy storage can clearly aid the impacts caused by the rebound effect. Increasing the BESS penetration in the system will decrease the rebounds even further. Also, with load leveling the peak demand to base demand ratio is improved as well.

3.11: Potential of Water Heater as Thermal Energy Storage Device

Water heaters with storage tank can be used to store thermal energy before the peak periods and can be left off during the peak period. Many utilities are trying to adopt the electric thermal energy storage (ETS) program for water heaters [29]. Water heaters can store energy which allows the water heater to be kept off for up to 6 hours.

On the day when DR response is expected, electric water heaters can be used to store thermal energy by increasing their setpoints. Due to high specific heat of water they would be able to maintain the water temperature above a certain desired value. The heat loss in the water heater can be calculated using,

$$Q = U * A * \Delta T \tag{13}$$

Here Q is the heat transferred or lost, U is the heat transfer coefficient, A is the surface area of the water heater and ΔT is the differences between the water temperature and ambient temperature.

Referring to Figures 3.18 and 3.19 it is certain that both diversified or unified DR signals for water heaters create rebound effects when 75% of the customers participate in the DR program. Hence a 75% participation case will be used to verify if the rebounds are completely mitigated using this strategy.

Figure 3.24 shows the algorithm used for using water heaters as thermal energy storage devices. The number of participants is equally divided into x groups. Depending upon the number of groups, different DR signals are created which trigger different EWHs at different times.

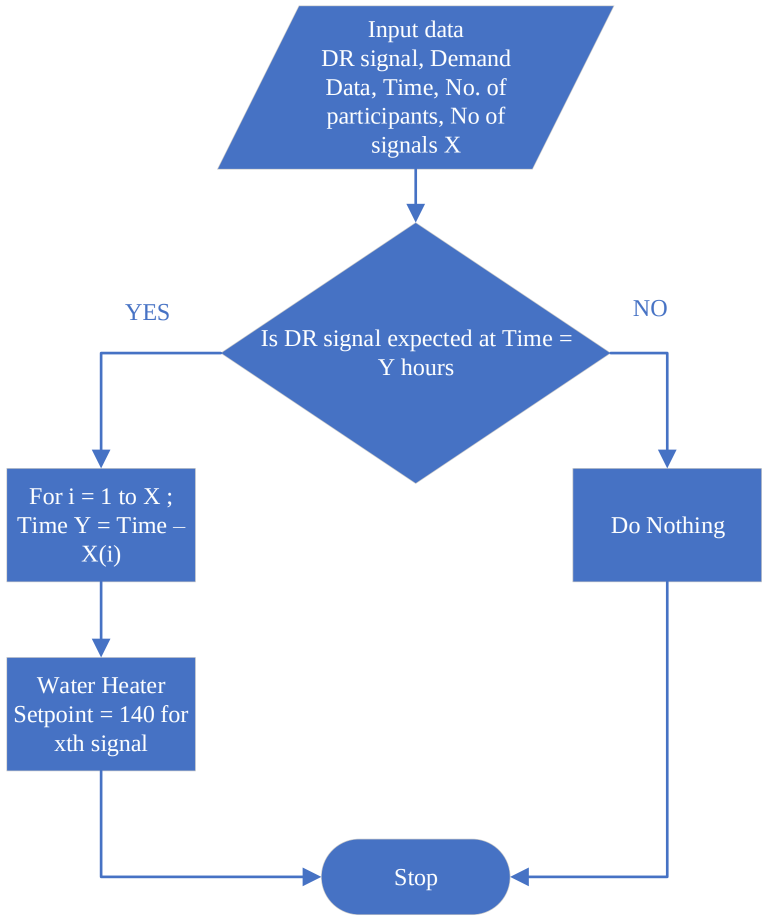

FIGURE 3.24: Water heaters as thermal storage devices

3.12: Case Study of Electric Water Heaters as Thermal Energy Storage and Rebound Mitigators

As mentioned before, rebound was evident for 75% adoption scenario hence, the application of EWHs as thermal storage was tested for 75% DR adoption scenario. It is considered that these EWHs are grouped into 5 different groups. Groups receive signal sequentially prior to the DR event to raise their setpoints for 1 hour. For example: Group 1 receives signal from 1pm to 2pm then group will receive signal from 2pm to 3pm. This continues until all groups receive signal.

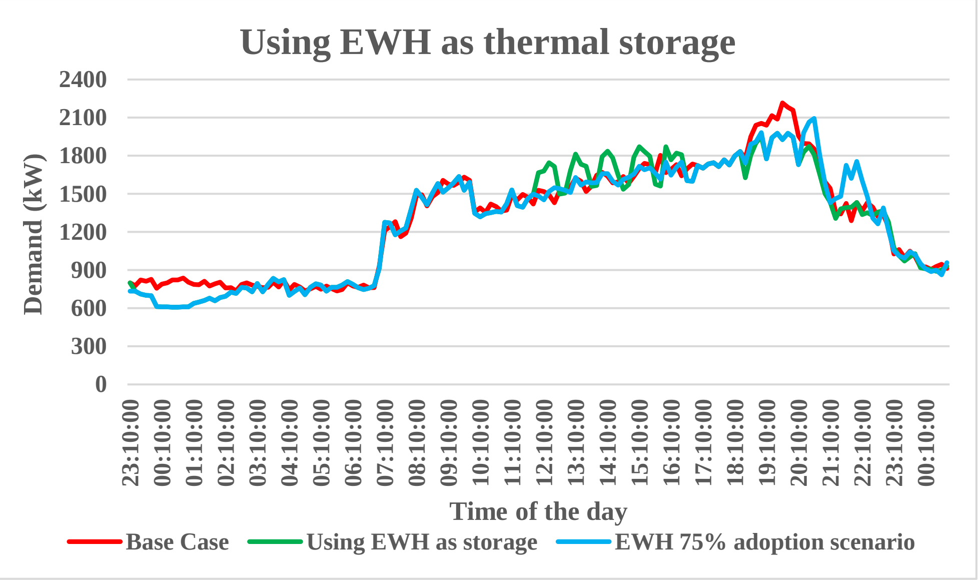

FIGURE 3.25: Using EWH as thermal energy storage

In the above Figure 3.25 which shows the use of EWH as thermal energy storage it can be observed that when EWH is used as thermal energy the demand increases from 12pm to 5pm. 5 Bumps are observed in the demand curve which represent the increase in demand for 5 groups. It can be observed that along with peak reduction rebounds are completely mitigated in this case, because water heaters are able to maintain their supply water temperature above a specified set point even after the DR event. This can be observed in the Figure 3.26 below. The water temperature never drops below 120 Deg F. Hence, this method helps support DR and rebound mitigation without affecting the consumer comfort. Also, from the usage pattern it can be observed that, the hot water demand during the afternoon is low hence, this wouldn’t affect the consumer’s activities significantly.

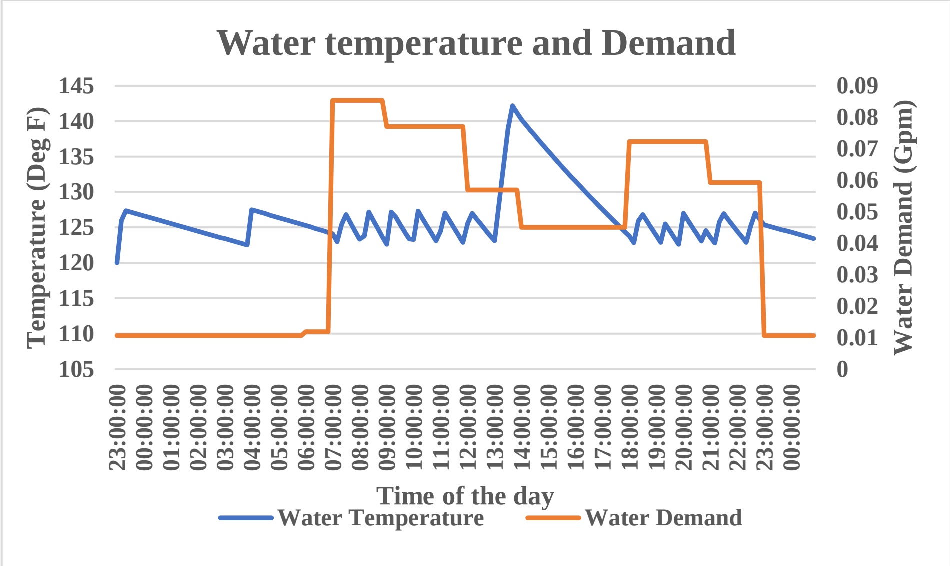

FIGURE 3.26: Water temperature and demand from water heater

3.12 Conclusions

1) This chapter discussed the appliances which have high potential for DR in residential buildings.

2) A comparison between the two thermostatically controlled flexible loads HVACs and EWHs was made, and difference in their operation and potential response that can be obtained from them was analyzed.

In the next chapter, impacts of this DR on the electric grid, mainly the distribution system, will be studied.

CHAPTER 4: : IMPACTS OF DR ON THE DISTRIBUTION SYSTEM

DR is bound to have some impacts on the electric grid. Some of the impacts on the system reliability are described in [57-59]. The loads used for DR are responsive loads and are flexible enough to provide ancillary services support to the grid. In fact, these flexible loads have a much faster response than conventional generating plants. DR can be used to support various ancillary services such as [58]:

i) Energy Imbalance- Load following and energy imbalance addresses the intra or inter-hour balancing requirement of the utility or the ISO. With the flexibility of the DR resources, they can provide the energy imbalance service to the grid by ramping up or ramping down the demand requirement. The response speed for these services is usually 10 minutes and the duration of their requirements is anywhere between 10 mins to hours[58].

ii) Operating reserves- These services are required in case of a contingency. The operating reserves include spinning, non-spinning and supplemental reserves.

   a) Spinning reserves: These are online reserves synchronized to the grid that can ramp their outputs upon receiving the signal. These resources must reach their maximum capacity within 10 minutes to comply with NERC's standard [58].

   b) Non-Spinning reserves: These resources are like spinning reserves, except that they are offline and must reach their output within 10 mins when called upon. They react after the spinning reserves.

c) Supplemental or replacement reserves: They have a slower response time and they are used to restore spinning and non-spinning reserves to their pre-contingency state [58].

iii) Frequency Regulation- These are online resources which respond to the automatic generation control and track the minute to minute fluctuations in the system load and correct these fluctuations [58]. These are fast ramping resources and are required to respond within a minute. Their response duration lasts for few minutes.

iv) Voltage Control and Reactive Power Supply- Reactive power supply is needed to maintain the voltage stability throughout the system. Loads with large solid-state drives could be able to supply this although this must be co-ordinated with the transmission provided [58]. Reactive power is local and hence the requirements are location specific when compared to the real power. This service is required for seconds and duration of this service is also anywhere between few seconds to few minutes.

Figure 4.1 shows the difference between the ancillary services based on their response speed and duration.

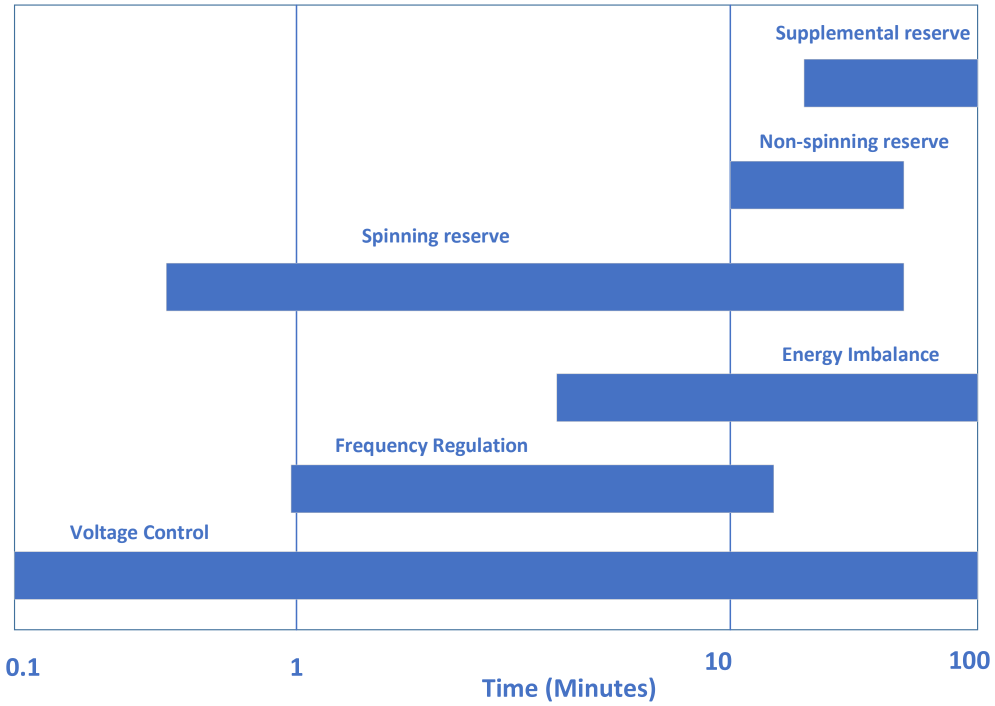

FIGURE 4.1: Ancillary Services based on response speed and duration

4.1: IEEE 37 Node Test Feeder

To test the impact of DR on the electric grid an IEEE 37 node test feeder model was developed to connect the residential loads and implement various DR strategies. Figure 4.2. below shows the schematic of this radial distribution feeder. This feeder is an actual real feeder located in the state of California. The system operates at a nominal voltage of 4.8 kV [60]. All the lines are underground cables. Loads can be connected as spot loads or distributed along the line section, but for this study all loads are connected spot loads and consist of constant current loads, constant impedance and constant PQ loads [60].

This base system was modified to connect the residential loads. These residential loads are spot loads and are connected as single-phase loads using a split-phase transformer to a triplex node. A cluster of houses is created and this cluster through a triplex line is connected to the node of the 37-node test feeder.

Using the triplex lines and transformers, 10 nodes were created with the provision to connect the residential loads. A specific criterion was not set for choosing these 10 nodes. Although it was kept in mind that whole most of the test system should be covered within these nodes.

There is one regulator connected between the substation node and node 701. This regulator is always connected to the system i.e the switch position is closed. The Figure 4.2 below shows the nodes with provision to connect residential loads. These nodes are colored red and a square box covering the node number is an indicator for such nodes.

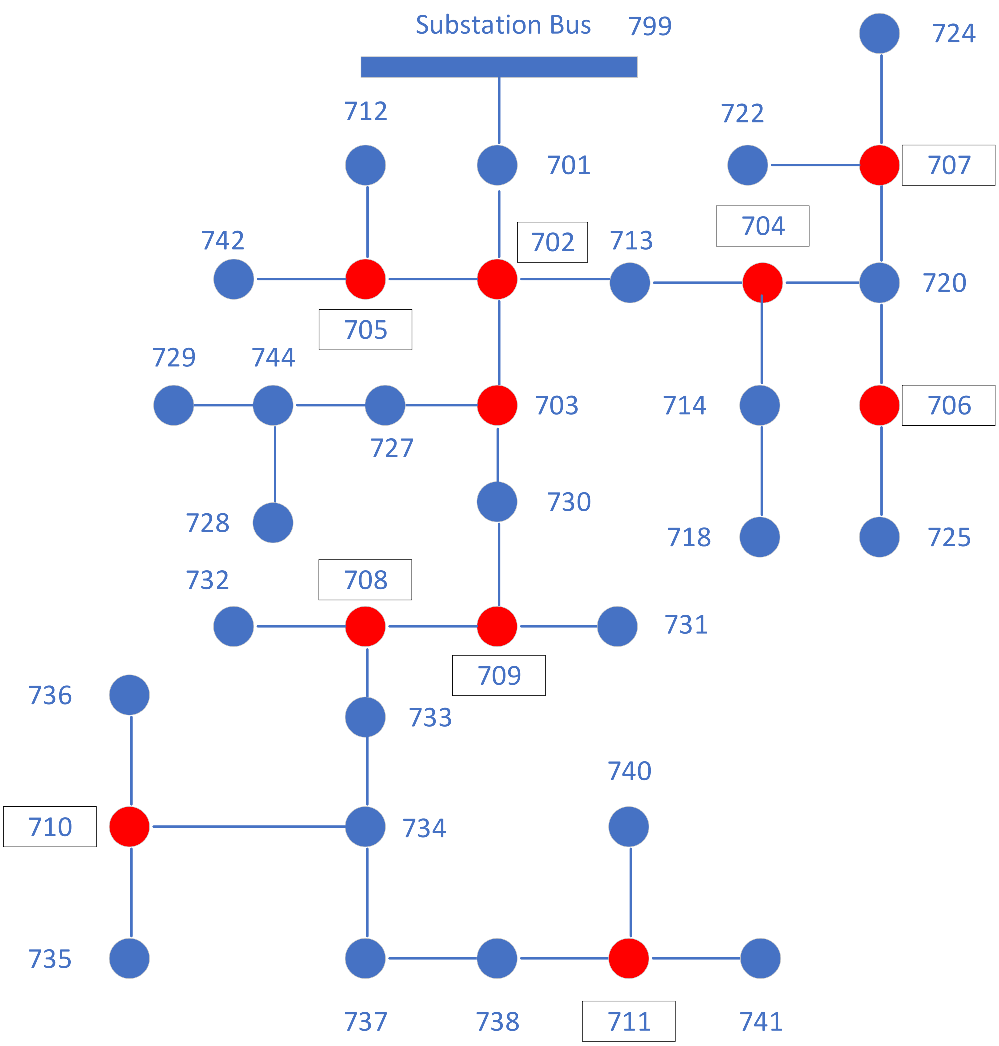

FIGURE 4.2: Nodes with provision to connect residential load

4.2: Thermostatically Controlled Loads as Operating Reserves

Spinning and Non-spinning reserves are called upon when there is contingency in the system, i.e., whenever a transmission line or a generator fails. These reserves are deployed automatically if the failure violates the system frequency outside the dead-band of the governor. If the real power interchange between control areas is impacted even, then operating reserves could be called upon. Smaller contingencies are addressed with frequency regulation [57, 58].

As explained in the previous section, according to NERC reliability standards, the response of spinning reserves should be within 10 mins and they should be able to provide this response for a maximum duration of 2 hours. Although, historically the contingency reserves are deployed for a much shorter duration with an average of 10 minutes. Table 4.1 shows some historic statistics related to deployment of spinning reserves:

TABLE 4.1: Spinning reserve deployment for various ISOs

RTO/ISO	Average Duration (mins)	No. of Deployments	Time Between Deployment (days)
NYISO (2002)	11	239	1.5
ISO-NE (2005)	11	19	19
CAISO (2005)	9	26	14

Thermostatically controlled loads such as HVACs and Electric water heaters have the capability to withstand numerous short curtailments and infrequent sustained curtailments. These loads are flexible enough to be rapidly restarted and curtailed immediately upon receiving the contingency signal. The characteristics that sets these loads apart from the conventional generators is that, these loads do not have constraints that the conventional generators possess, such as, there is no ramp time and minimum on or minimum off time.

These characteristics make TCLs more superior than the conventional generators for providing spinning reserves. The consumption curtailment is more rapid than ramping up the generation. The only time delay involved in this process is caused by the control signal to get from the system operator to the load. This time delay is well within the 10 minutes duration allowed for generation to fully respond [58].

Furthermore, using these TCLs for supplying contingency reserves is much more practical and feasible as compared to providing peak shaving since the duration for which response is required is much shorter and the response frequencies are less as well. For peak shaving these TCLs are required to respond for multiple hours per day also it is quite possible that these loads are called upon for several days in a row. These could put some constraints on the customers participating in the peak shaving DR program. For example: Peak load reduction is required at the same time when HVAC functioning is required.

For providing contingency reserve requirements these flexible loads should be available to respond immediately whenever a contingency occurs and can continue to operate normally otherwise. Supplying fast responding ancillary services is economically beneficial since the value of these ancillary services is based upon response speed rather than duration.

The price of contingency reserves is highest when the demand is very high, hence it makes sense to use these TCLs as operating reserves when the demand is at or near peak value. During the low load condition, the base or intermediate generators have enough capacity to support the contingencies.

4.2: Methodology to Determine the Potential of TCLs as Operating Reserves

The available operating reserves capacity from the TCLs depends upon several factors and there is much uncertainty involved. The aggregated capacity from the air conditioners is evaluated in a several articles. The response capacity, duration and ramp rate quantified in [61]. Using temperature set back strategy, the HVAC response and their operation characteristics of individual and aggregated air conditioners are analysed in [62]. DR management approach is proposed for controlling DR duration time and capacity by considering temperatures [63]. Figure 4.3 describes the proposed architecture for evaluating the operating reserves capacity. The approaches mentioned earlier do not consider the actual HVAC operation based on the climate. Also, some of the approaches do not consider the uniqueness among the HVAC devices such as the variation in their fuel source, size of HVAC and so on.

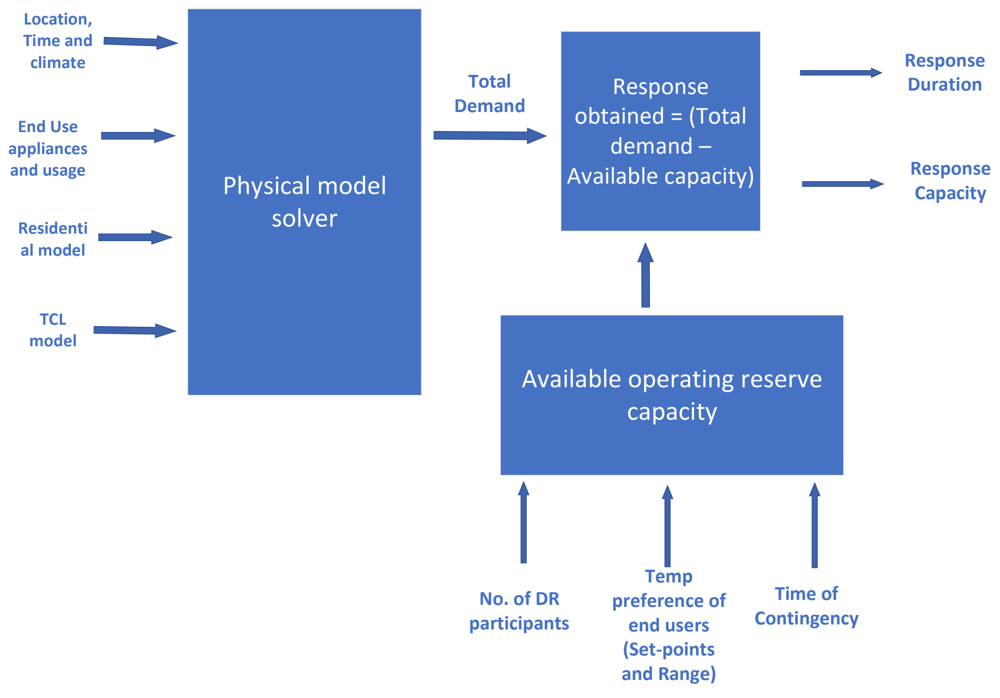

FIGURE 4.3: Operating reserves capacity architecture

Using the original base system model, the total demand at a particular time is calculated. This total demand includes the TCL demand. The available operating reserve capacity at any moment will be dependent upon the number of customers willing to participate in this program, their temperature preferences such as their current setpoint, and the range by which they are willing to offset their setpoints. The time of contingency will decide the available HVAC capacity as well. Response capacity is mainly dependent upon the no. of participants and the time of contingency. Whereas, the duration of response is based on the temperature range, by which these participants are willing to offset their setpoints.

Various cases are designed to test the potential of these TCLs for provide operating reserves. Like DR, four participation scenarios are created. 25% adoption, 50% adoption,75% and 100% adoption to the program. These participation scenarios are tested at various time of the day.

4.2.1: Case Study

As mentioned before, various the potential of TCLs to serve as operating reserves (spinning and non-spinning reserves) is tested. Contingencies are created at different times during the day. For off-peak period 2am was chosen since demand during this time is very low. For peak period 7pm was chosen as demand is highest during this hour. Morning period when demand is high, but the weather conditions are moderate might produce different effects to test this 10am was chosen as time when contingency occurs. For testing the potential during afternoon hours 1pm was chosen.

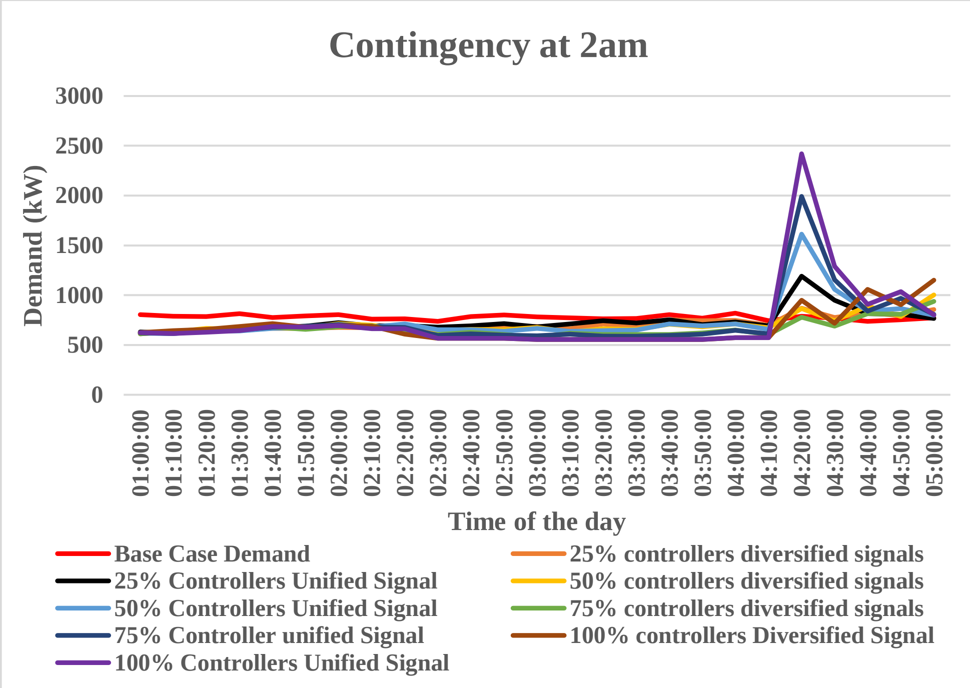

FIGURE 4.4: Contingency at 2am

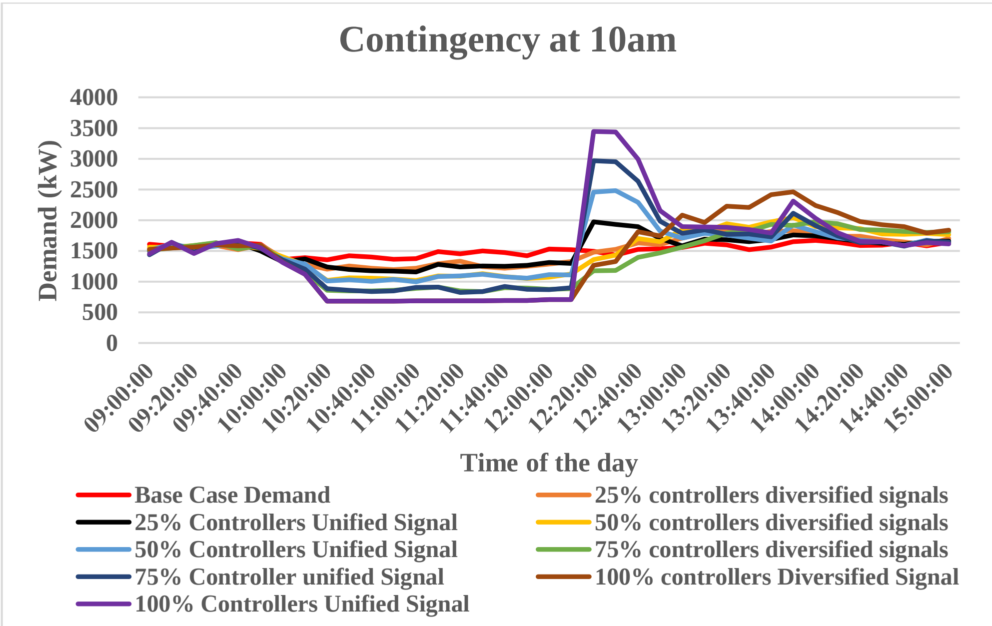

FIGURE 4.5: Contingency at 10am

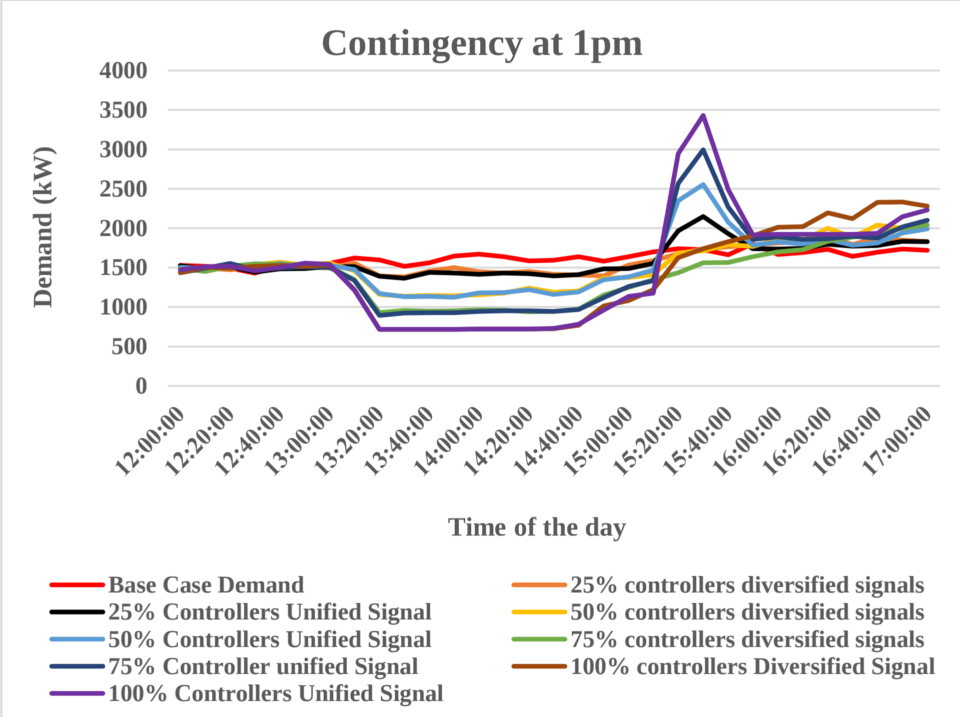

FIGURE 4.6: Contingency at 1pm

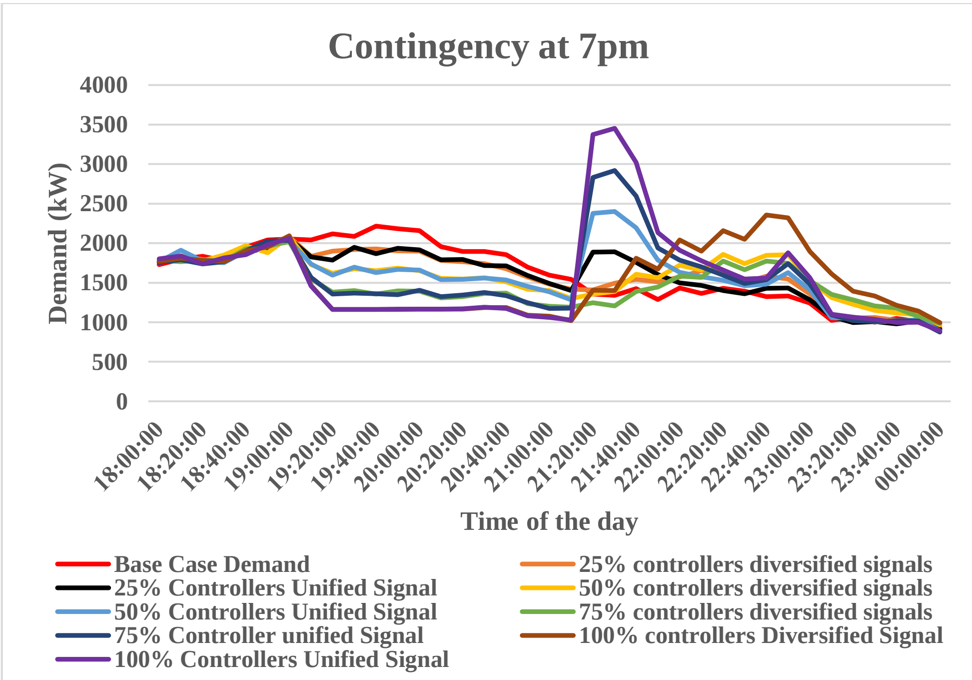

FIGURE 4.7: Contingency at 7pm

The above Figures 4.4 to 4.7 shows contingency at various times of the day and from them it is observed that response of TCLs is unique for each case. The response duration and capacity are dependent various exogenous factors like weather and human behavior. It is clear that use of TCLs during off peak periods like 2am isn't feasible as the response capacity is very low and unnecessarily rebounds would be created. In all these case DR signals were sent for 3 hours and 10am in the morning provided the maximum response duration. This is due to the fact that, the weather conditions were not extreme and available TCL capacity was high as well. Even during the peak period at 7pm in the evening, TCLs provide the 2 hours response also, the capacity obtained is highest int this case.

Unified signals create peaks higher than the original system peak in almost all cases. Hence diversified signal should be used to bring back these resources online. For off-peak period even diversified signals would create peaks higher than the case indicating inefficiency of TCLs to provide operating reserves during off-peak periods. For peak periods even with 75% DR participation higher than system peak rebounds are not observed.

From the results above, the use of TCLs as operating reserves can be justified as they match all the required criteria. Although, during off-peak period it makes more sense to use the utilities available generation as most of the cheaper generators are available for dispatch.

4.3: Impact on System Voltage

As, voltage is inversely proportional to the current, when electrical load increases the current drawn increases, and this creates a drop in the voltage. Various voltage regulation methods are discussed in [64]. Conventional methods involve use of on load tap changers (OLTC) which maintains a stable secondary voltage by effectively selecting tap positions. The tap change position usually takes anywhere between 3 and 10 minutes and several minutes between frequent operations [64]. Another method includes large synchronous generators that can control voltage levels by adjusting their output. More modern techniques involve use of shunt capacitors is usually done to supply the reactive power in response to the voltage drop and shunt reactors to lower the voltage [57].

In this section, the use of TCLs to provide voltage support has been tested out. By curtailing the load during high demand hours, voltage drop can be mitigated. For this purpose, the residential houses are connected to the IEEE 37 node test feeder described in section 4.1.

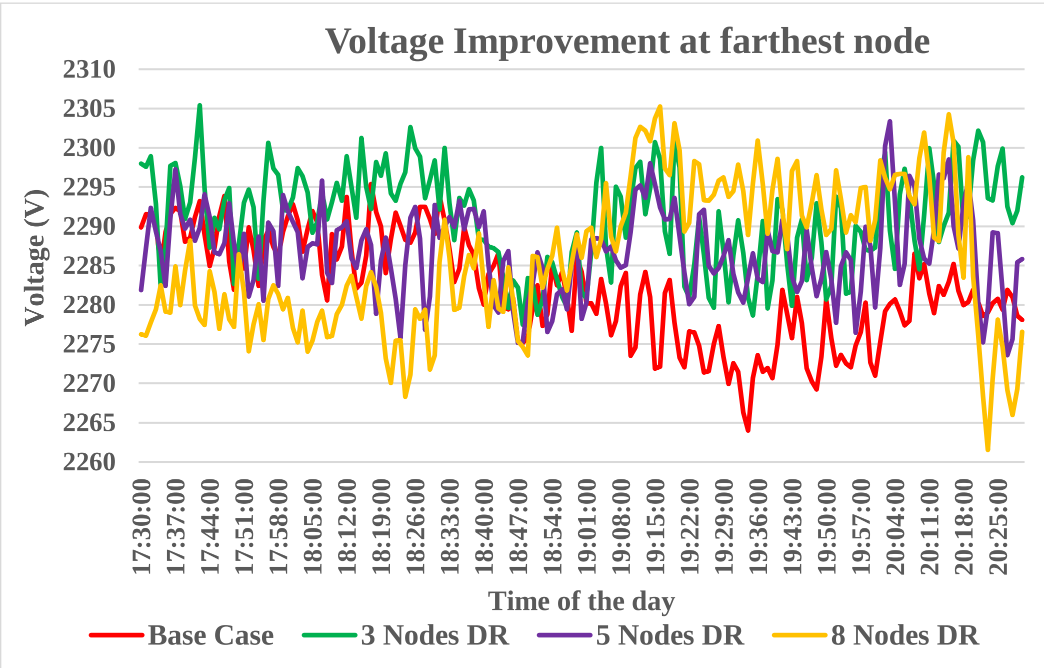

FIGURE 4.8: Improvement in voltage profile during the DR event

From the above Figure 4.8, it is evident that, voltage drops during the peak periods during the base case in which no DR program is implemented. Thus, with DR the peaks are reduced and hence an improvement in the voltage profile is observed. Figure 4.9 shows that increase in the DR participants decreases the voltage drop. Hence, the voltage profile smoothens and any plummets in the voltage are mitigated.

Although, the rebound created by the TCLs can cause violation in voltage drops as it can be seen below in Figure 4.9. When large number of customers participate in any DR program care should be taken that, rebound mitigation measures are considered as well.

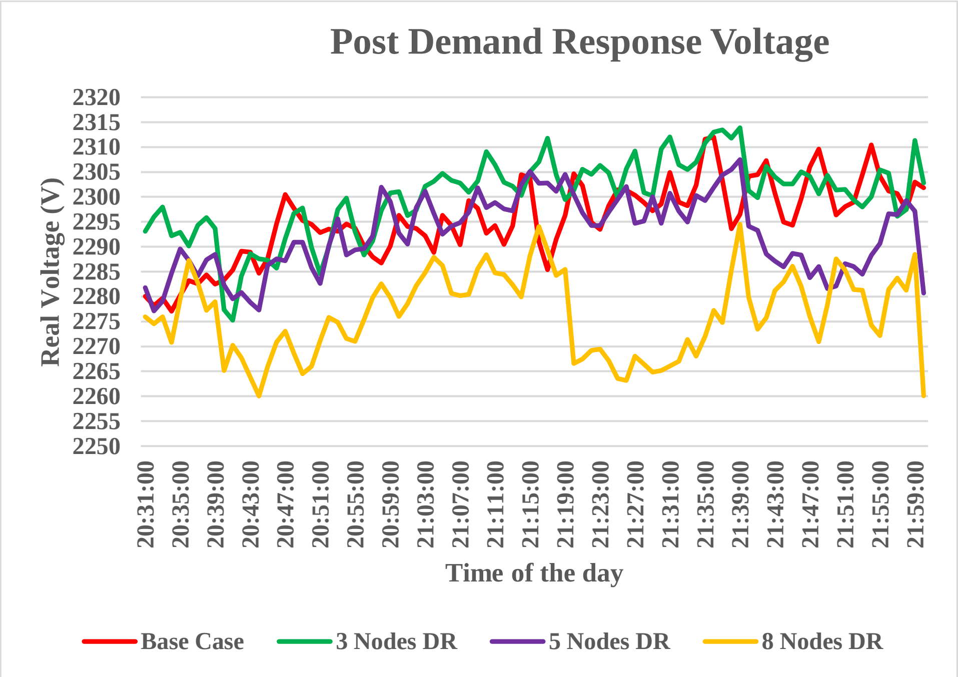

FIGURE 4.9: Voltage post DR event

Tables 4.2 and 4.3 display the summary of the results for voltage improvement during DR event and adverse effects on system voltage if rebounds are not mitigated.

TABLE 4.2: Voltage improvement due to DR

Scenario	Minimum Voltage (P.U)
Base Case (No DR)	0.9433
3 Nodes DR (30% penetration)	0.9494
5 Nodes DR (50% penetration)	0.9485
8 Nodes DR (80% penetration)	0.9515

TABLE 4.3: Adverse effect on voltage due to rebound effects

Scenario	Minimum Voltage (P.U)
Base Case (No DR)	0.9487
3 Nodes DR	0.9480
5 Nodes DR	0.9488
8 Nodes DR	0.9416

From the above Tables 4.2 and 4.3, it can be observed, that due to high demand there is violation in voltage limits. With DR the voltage drops are reduced and hence an improvement in the minimum voltage is observed. However, if proper actions to mitigate the rebound are not taken, an adverse effect on the system voltage could be observed.

4.4: Impact on Line Losses

Since losses that occur in the power system lines are proportional to the square of the current, any load shifts from peak to off-peak period will result into a net reduction in T&D losses. Mathematical formulation for these loss savings due to load leveling has been studied in [65]. Techniques for mitigation of these losses using hysteresis band current controlled based STATCOM has be proposed in. Another approach discusses about optimum placement of capacitors and optimum voltage setting of generators and SVC placement for reduction in line losses [66, 67]. In this study use of flexible residential loads to reduce the peaks has been used as a tool to reduce the line losses. Any shifts in the peak demand will create a squared reduction in line losses. To test methodology, IEEE-37 node test feeder is used for simulating various cases.

Since all the residential loads are connected at distribution system, the equivalent impacts will be observed on the transmission system as well. Loss savings in both T&D systems will be observed. Below Figure shows the impact of DR on losses in the system.

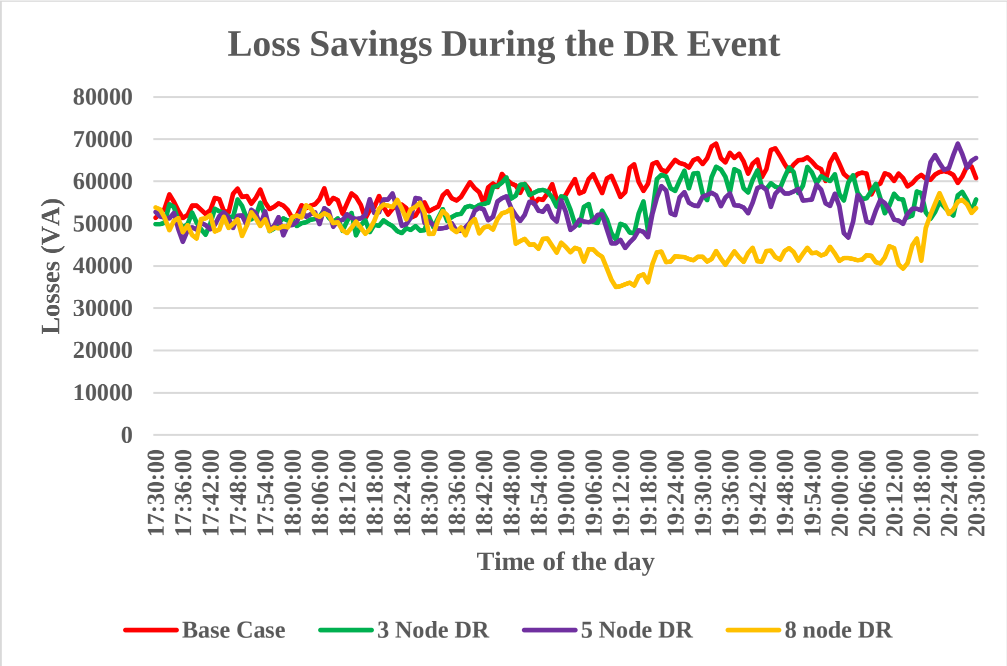

FIGURE 4.10: Impact of DR on system losses

It can be observed from the above Figure 4.10 which indicates the impact of DR on system losses that, when load increases during the peak period losses increase. Base case is case without any DR and hence, has the highest losses during the peak period. As, the number of nodes where DR was carried out increases the savings in these losses increases as well. It is evident that, when 8 nodes participated in the DR program these losses were lowest.

Although, when DR is carried out with thermostatically controlled devices there is a chance of rebound. This rebound can cause peak shifting and these new system peaks could be greater than the original system peaks. Hence, the impact of these rebounds on system losses was studied as well. Figure 4.11 shows the impact on system losses if rebounds are not mitigated.

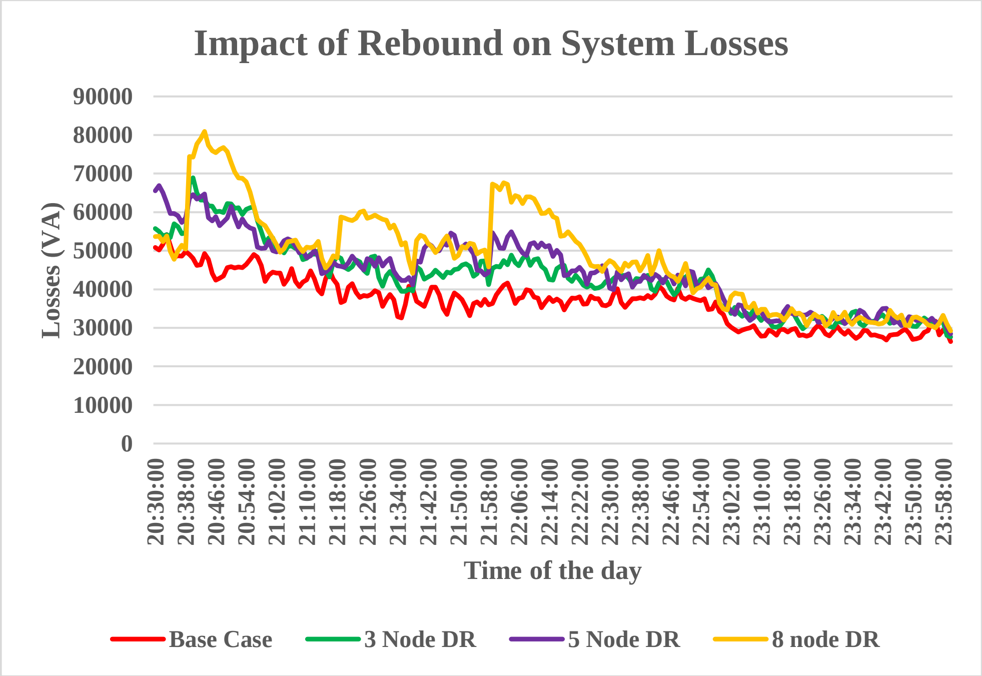

FIGURE 4.11: Impact of rebound on system losses

Thus, from the Figure 4.11 above, it can be observed that the losses during DR scenarios are much higher than the base case. This is because of the rebounds created by the thermostatically controlled loads and hence, mitigating these rebounds is very important. Increase in the DR participants could create greater losses as observed from the above Figure 4.11.

TABLE 4.4: Loss Savings for 3 hours due to DR

Scenario	Losses (VAh)	Loss Savings
Base Case (No DR)	177511.8	-
3 Nodes DR (30%)	164153.1	7.5%
5 Nodes DR (50%)	160492.9	9.5%
8 Nodes DR (80%)	140655.5	20%

TABLE 4.5: Adverse impacts on losses due to rebound effects

Scenario	Losses (VAh)	Excess Losses
Base Case (No DR)	115471.6	-
3 Nodes DR (30%)	135609.9	14.8%
5 Nodes DR (50%)	140443.7	17.7%
8 Nodes DR (80%)	153829.5	24.9%

As observed from the above Tables 4.4 and 4.5, DR could create loss savings if implemented properly. Although, there is a risk of increase in losses if rebounds are not mitigated. These losses incur due to sudden inrush currents from the motors of the devices that respond in unison to the DR signal.

4.6: Conclusion

In this chapter various impacts of DR on the grid were studied. These impacts provided a different perspective on how these flexible resources can be deployed rather than just implementing them for peak shaving or load leveling applications.

CHAPTER 5: BENEFITS OF DR

In section 1.6 costs and benefits of DR are discussed briefly. Success of any program will be determined by the net benefits it produces. The benefits produced by DR depends upon the type of the DR program as well as the market structure it is implemented in [DOE]. In this chapter 5, detailed framework for deriving some of the components is proposed. Only utility's perspective is considered for developing the methodology of these components.

As evident from chapters 3 and 4 that DR not only produces reduction in peak demand but also provides various other benefits. Following benefits were identified to have a maximum impact and hence, this study will be limited to those components only. The components are:

1) Avoided Energy
2) Avoided Generation Capacity
3) Avoided Transmission and Distribution Capacity
4) Avoided System Losses
5) Environmental Benefits
6) Operating Reserves Capability
7) Voltage Support

All of the above-mentioned benefits can be obtained from the models developed for the DR. Most of the components are evaluated for their annual benefit. It is assumed that, the number of participants in DR programs are fixed so that the available capacity is fixed.

5.1 Avoided Energy

The benefits associated with energy are primarily obtained due to the avoided energy from peaking generation units. Usually, a production cost model which has unit commitment and economic dispatch abilities is used to quantify this benefit [68, 69]. In this study an alternative approach is proposed which simplifies the methodology as well as omits the need for using a production cost model [70]. Two cases are developed; one with DR and one without DR. Difference between these two cases would give the avoided energy benefits. Benefits obtained during peak period are associated with the operating costs and energy reduction during that period. These are given by equation 14, below:

$$Energy\ Savings\ (\$) = \ Operating\ costs\ of\ peaking\ plants\ \left(\frac{\$}{KWh}\right) * Reduction\ in\ energy\ (KWh) \qquad (14)$$

As we know that post DR event the appliances try to recover back to their normal state and hence, can consume more than normal energy. This excess consumption costs are given by equation 15 below,

$$Excess\ consumption\ cost\ (\$) = \ Operating\ costs\ of\ base\ plants\ \left(\frac{\$}{KWh}\right) * Increase\ in\ energy\ (KWh) \qquad (15)$$

The net benefit is obtained by subtracting equation 15 from equation 14.

$$Avoided\ Energy\ = \ Energy\ Savings - \ Excess\ Consumption\ cost \quad (16)$$

Running annual simulations would give annual benefits obtained from DR.

5.1.1 Case Study

Annual avoided energy was obtained using the methodology describe in section 5.1. DR would be implemented on peak days only and these peak days would occur during extreme seasons; summer and winter. Hence, three summer months from June to August are considered whereas, for winter December to February are considered for analysis.

Random days - 15 days per month are selected from these months and two cases, with and without DR are run for each day. The avoided energy calculated is averaged and multiplied over 30 days to get the avoided energy over that month. This step is repeated for every month. This methodology and assumptions will be applied to all other components mentioned below.

Results for a sample peak day are given below in Table 5.1. Using equations 14, 15 and 16 the results are evaluated. The variable O&M costs were obtained from EIA levelized cost and levelized cost of generation 2019 report.

TABLE 5.1: Avoided energy costs for 1 day

With DR	Value	Without DR	Value
Energy consumption during peak period (KWh)	8403.947	Energy consumption during peak period (KWh)	8722.895
Energy consumption during recovery period (KWh)	4195.423	Energy consumption during recovery period (KWh)	3979.705
Variable O&M costs during peak period ($/KWh)	0.052	Variable O&M costs during peak period ($/KWh)	0.052
Variable O&M costs during recovery period ($/KWh)	0.031	Variable O&M costs during recovery period ($/KWh)	0.031
Avoided energy during peak period (KWh)	318.94		
Excess energy during recovery period (KWh)	215.71		
Avoided energy costs ($/KWh)	9.985		

5.2 Avoided Generation Capacity

The primary goal of DR is to reduce the system peaks. This would decrease the need of adding new generation. DR will displace some of the conventional centralized generating plants. Although, DR is obtained from flexible loads their availability is uncertain due to numerous factors. This means that DR can displace only a certain percentage of generation capacity. This percentage is known as the capacity factor of that resource. There are numerous methods which can compute the capacity factor. Effective load carrying capability (ELCC) is most effective method that estimates the amount of capacity DR can contribute reliably [70-72]. Like 5.1, for this component 2 cases are developed; with DR and without DR. Difference between these two cases would give the avoided generation capacity.

$$ELCC = \frac{Demand\ met\ without\ DR\ (kW) - Demand\ met\ with\ DR\ (kW)}{Available\ DR\ capacity} \tag{16}$$

$$Avoided\ Generation\ Capacity\ (kW) = ELCC(\%) * Total\ DR\ Capacity(kW) \tag{17}$$

$$Avoided\ Generation\ Capacity\ Costs\ (\$) = Avoided\ Generation\ Capacity\ (kW) * Cost\ of\ marginal\ generators\ (\frac{\$}{kW}) \tag{18}$$

As DR would be required only during the peak days, simulations for extreme weather months are performed where the chance of having peak demand is most probable. For summer months random days from June and July are selected for winter December and January are selected.

5.2.1 Case Study

Like avoided energy, the process of simulating random days per month is repeated. Using the methodology defined in 5.2, the avoided generation capacity costs are evaluated for 25% adoption in DR.

Table 5.2 below summarizes the results obtained for avoided generation capacity during summer season.

TABLE 5.2: Avoided generation capacity costs in summer

Maximum capacity reductions due to DR (kW)	390
Average capacity reductions due to DR (kW)	252
Effective load carrying capability of (%)	64%
Percentage reduction peak generation in capacity	11.3%
Avoided generation capacity costs ($)	23,184

5.3 Avoided Transmission and Distribution Capacity

Like avoided generation capacity, transmission and distribution will have an equivalent impact. All residential loads are located on the distribution system hence, a kW reduction on distribution system will be reflected on transmission system as well. A methodology similar to 5.2 is developed. Marginal cost of T&D due to load growth are used derive the benefit.

5.3.1 Case Study

The results from 5.2.1 are applied to avoided transmission and distribution capacity as well. The only difference being that marginal costs of transmission and distribution are considered instead of generators [73]. Since, the peak reduction is observed at substation level the distribution and transmission system impacts would be similar to generation.

Table 5.3 provides summary for avoided T&D costs.

TABLE 5.3: Avoided T&D costs

Maximum capacity reductions due to DR (kW)	390
Average capacity reductions due to DR (kW)	252
Effective load carrying capability of DR (%)	64%
Percentage reduction in peak transmission and distribution capacity	11.3%
Avoided T&D capacity costs ($)	12,600

5.4 Avoided System Losses

As observed in section 4.5, DR reduces the line losses. Using the results obtained in that section loss savings can be derived as,

$$Loss\ savings\ (KWh) =$$
$$Losses\ without\ DR\ (KWh) - Losses\ with\ DR\ (KWh) \quad (19)$$

5.5 Environmental Benefits

DR will reduce the need for energy from inefficient peaking plants. These plants usually emit large amount carbon dioxide. DR will reduce the of generation from these plants.

$$Avoided\ Carbon\ \left(\frac{\$}{KWh}\right)$$

$$= \frac{\left(Avoided\ carbon\ emissions\ (MT)\right)}{Total\ energy\ reductions\ due\ to\ DR\ (MWH)}$$

$$*\ Social\ cost\ of\ carbon\ \left(\frac{\$}{MWh}\right)$$

(20)

5.5.1 Case Study

Using the emission and generation resource integrated database (eGRID) per unit emission for each type of peaking plants were obtained. In this scenario, since the assumption is that, natural gas plants are peaking plants emissions for those plants would be used. Using equation 20 the value for avoided carbon could be evaluated. A sample one day avoided carbon is calculated in table 26 below.

TABLE 5.4: Avoided carbon dioxide for one sample day

Emissions for NG plant (Lbs/MWh)	926.53
Social cost of carbon ($/MWh)	40
Total reduction in energy (KWh)	103
Avoided Emissions (MT)	0.043
Avoided Carbon ($/MWh)	16.69

5.6 Operating reserves capability

As discussed in chapter 4, DR being a flexible resource has ability to supply operating reserves. Hence, a need for maintaining additional operating reserves would be reduced. The benefit obtained from this component will be associated with the marginal operating costs of these contingency generators.

5.7 Voltage support

In chapter 4, it is observed that with DR the voltage at farthest node improves. This effect is observed on the whole system. Hence, need for additional voltage support equipment could be deferred. The benefit obtained from this component will be associated with the costs of these additional equipment such as capacitors and voltage regulators.

5.8 Costs of DR

In this study the costs of DR have not been included as they are subjective to the utility. Referring to table 1.2 it can be observed that these costs are associated with, cost of equipment such as modern communication technologies as well as the costs incurred from educating the customers and marketing/promoting the DR programs. These costs are subjective and would depend upon the willingness or the expenditure power of the utility. For example, bigger utilities with more spending power could invest more in the state of art technology whereas smaller utilities could choose technology just enough to meet the requirements. Some utilities could promote the DR programs through expensive digital communication whereas some would just distribute informative brochures.

Although, these costs are important as they would decide the participation in DR program and define its success. No framework to quantify these costs from DR has been established yet and hence, a comprehensive study in future could help determine it.

CHAPTER 6: CONCLUSION AND FUTURE SCOPE

DR in residential buildings could play a major role by maintaining a supply demand balance of the grid of the future. Residential buildings have a huge potential to provide DR and still most of it is still untapped. Higher participation in DR program would produce greater benefits. Although, a proper care to mitigate the rebounds during recovery period should be taken.

In this study, DR strategies on thermostatically loads are performed primarily. Although, with better communication capabilities for other end-use devices it would be possible to perform DR using those devices as well. For example, changing the duty cycle of the refrigerator during peak periods or shifting the schedule from peak to off-peak period would also create similar effects. Decreasing cost of batteries makes it a leading candidate to support DR programs in future.

Apart from peak shaving or load leveling DR also provides several other benefits. DR also provides ancillary service support such as operating reserves, frequency regulation and voltage support. Flexible loads make DR a better option than conventional generator to provide these services. These services can generate various value streams for the stakeholders making DR a lucrative option.

DR also provides capacity related benefits to the utility. Implementing a comprehensive DR study in the resource planning would yield better benefits. These benefits would save several expensive infrastructure investments. Energy related benefits would be achieved by both customers and the utility/ISO. Avoiding or reducing the use of peaking plants would also create environmental benefits for the society. A comprehensive study would be able to determine the exact value of DR. This would help stakeholders make investment decisions and help in increasing the societal benefits. A real-time tool could also help assess the impact of DR on the grid and with help of modern communication technologies load could be adjusted in the real-time during the DR period which will improve the system stability and reliability. Integrating DR with distributed energy resources would yield maximized benefits by reducing the stress on the grid and improving the system reliability. Using these flexible resources, it would be possible to shift the paradigm from generation following the load to load following the generation.

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