Impact of Elasticity in Domestic Appliances on Aggregate Residential Power Demands

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Power grids in today's developed societies are designed to meet consumer demands in a highly reliable manner. In order to guarantee reliability to consumers, the grid is required to be sized for infrequently occurring demand peaks. The cost of maintaining generation sources that make up the relatively unused capacity of the grid can be extremely high. In addition to high costs, environmental impacts of these sources are also of great concern. In order to serve highly fluctuating peak demands, energy sources such as coal, gas and bio-gas are commissioned by utilities. These sources have a high carbon footprint.

In order to prevent wasting extensive amounts of money in maintaining infrequently used grid capacity and causing an adverse environmental impact, a comprehensive study on how elasticity of domestic appliances can be used to reduce the impact of these issues is made. A thorough analysis of appliances in four distinct regions is presented. Significant reduction of peak demands is shown quantitatively for all of the four regions. Based on these positive results, an elasticity based scheme that takes into account user discomfort is proposed for reducing monetary and environmental issues faced by today's utilities.

Acknowledgments

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Table of Contents

List of Tables

List of Figures

Chapter 1

Introduction

Power grids in today's developed societies are designed to meet consumer demands in a highly reliable manner. According to [2], power grids guarantee outage of services to occur only at most once in 10 years. This translates to a 99.96 % up-time.

In order to serve consumers in such a highly reliable manner, the grid is required to be sized for infrequently occurring demand peaks. According to [1], in Ontario, 7% of the grid's capacity was unused 99.6% of the time in 2006. The cost of maintaining generation sources that make up the relatively unused capacity of the grid can be extremely high. For example, in Ontario, a reduction in peak demand by 25% can result in savings of upto $27 billion over a period of 20 years [1].

Generation sources that are dispatched to serve highly fluctuating demand peaks need to be dynamic and must be engaged with short notice. Electricity is generated from a wide mix of energy sources that include fossil fuels (coal, natural gas, diesel), renewable sources (wind, solar, hydro) and nuclear power. Fossil fuels impose a high carbon footprint and can cause negative environmental impacts. Renewable sources such as wind and solar are clean but may not be consistently available. Hydro power is consistent, however, there are geographical constraints due to the extreme inefficiencies still present in transmitting and distributing power across long distances. Currently, fossil fuels are the energy sources used predominantly to serve demand peaks. Cleaner energy such as nuclear and hydro are relatively constant and therefore are used to serve the base load which is relatively constant.

Power demand patterns are highly correlated within a certain geographic region. Factors contributing to demand peaks in a region can include climate, behavioral patterns and local economy. For example, seasonal changes such as dips in temperature during winter, which will affect the region fairly uniformly, can cause residents to turn on their heaters simultaneously. If penetration rates of electric heaters are high in that region due to local energy policies, the utility can experience a sudden spike in power demand at that time.

In order to avoid wasting extensive amounts of money in maintaining infrequently used grid capacity and to prevent adverse environmental impacts caused by having to provision for fluctuating power demands with high carbon footprint energy sources, a novel method based upon a new property in appliances called elasticity is proposed in this work. This work focuses primarily on the residential sector as it represents almost a third of overall power demand in countries such as Canada, United States, France and India [3], [4], [5], [6].

This thesis can be divided into two parts. In the first half of this work, the characteristics of common appliances such as individual components, penetration rates and usage patterns are explored in depth. In order to understand the differences in the attributes of appliances due to cultural and political reasons, a detailed study is made for four different regions that include Ontario, Quebec, France and India. Then elasticity in appliances is introduced and defined. A preliminary analysis is performed for all four regions to estimate the potential of appliance elasticity. In the second half of the paper, a distributed solution for appliances that capitalizes on this characteristic to reduce aggregate power demands above a threshold in a region is presented.

1.1 State of the Art

Techniques to shave peak aggregate power demand in residential, commercial and industrial sectors have been well explored and some of these have been practically implemented in recent years.

Looming threats of climate change, extensive costs to maintain power generation plants, depleting energy sources and exponentially increasing penetration of electrical appliances and machinery are driving factors for initiatives taken by governments to reduce overall energy and power demands.

Initiatives taken thus far to reduce peak power demands can be categorized into three general classes:

- Smart appliances
- Demand response schemes implemented in the real world

- Demand response schemes in research

In the following, state of the art solutions in each one of the three classes identified above will be discussed in detail.

1.1.1 Smart Appliances

Techniques in this category mainly focus on modifying the behavior of appliances in response to some signal. Comprehensive reports on traditional appliances can be found in [4], [7], [8], [9], [10]. There are two distinct types of appliances in general. One set of appliances have a fixed duration of operation. Examples of these are dishwashers, washing machines and dryers. It is possible to know beforehand the duration required for these appliances to complete their operation. The other set of appliances work to maintain thermal inertia in an environment. Examples of these are fridge, space heaters and air conditioners. These appliances have internal components that are activated when the ambient environment falls above or below a pre-specified temperature setpoint.

Smart appliances are appliances with added computational intelligence. The intelligent component can delay the start time of appliances which have fixed operation duration to periods with lower electricity costs [11]. The delay start action cannot be applied to appliances that respond to thermal inertia as this can introduce *payback effects*. Payback effect refers to a situation where appliances consume more energy than typically necessary. For example if the start time of a heater is delayed by a few hours, then the house would have cooled down significantly. The energy required to bring the home back to the desired temperature may require more energy than necessary if the heater had not been shut off. An intelligent component, in these cases, can adjust the temperature setpoint so that the electrical components are minimally activated during periods of high electricity costs [12].

Although the smart appliances modify their behavior to minimize the cost of electricity, they do not explicitly take into account possible discomfort that can be introduced to consumers due to these modifications. For example, delaying the start time of a washing machine to a time that is late in the night can disturb individuals who are sleeping at that time. Decreasing the temperature setpoint in a house during winter can cause discomfort to its occupants.

Other possibilities on modifying the behavior of smart appliances have been analyzed and reported by the Smart-A project [13]. This project has conducted a comprehensive analysis of ten commonly found domestic appliances with load profiles and penetration rates for France. It also makes some interesting suggestions on how appliances can be made smarter. None of these suggestions use the elasticity property of appliances introduced in this thesis.

1.1.2 Demand Response Schemes in Practice

Utilities have introduced variable electricity pricing schemes to modify the behavior of consumers. *Price-based* and *incentive-based* schemes are the two main types of demand response schemes used by utilities [14].

Time of Use (TOU) falls under price-based schemes and is used predominantly in the residential sector. The hourly price of electricity is decided by the utility and is made known to residential consumers the day before it is implemented. Utilities hope that setting higher prices during peak periods will serve as negative reinforcement for consumers, leading them to schedule the use of their electric appliances during periods with lower costs (corresponding to non-peak periods). Two other price-based schemes include *Real-Time* and *Critical Peak* pricing (RTP and CPP respectively). Pricing for TOU is computed using average hourly generation costs whereas pricing for RTP is computed and updated on an hourly basis based on actual generation costs. CPP prices electricity during peak periods with a much higher cost than RTP. CPP and RTP schemes are typically used for industrial and commercial consumers [14].

Incentive-based schemes require utilities to forge contracts with industrial and commercial consumers. If demand side participants comply with the contracts, they are awarded with monetary compensations from the utilities. Otherwise, they will be penalized. Examples of incentive-based schemes include *Direct Load Control* (DLC), *Demand Bidding* (DB) and *Emergency DR (EDR)*. DLC allows utilities to directly control appliances. For example, air conditioners in a commercial buildings can be regulated by the utility. The utility can decide on the scheduling of appliances based on the solution to a complex optimization problem formulated according to factors such as the availability/cost of generation resources. The DB scheme involves consumers placing bids on wholesale market prices. The EDR scheme requires consumers to shed their loads immediately whenever the utilities inform them to do so. Most of these schemes are not trivial to implement and hence have been discontinued during early stages of implementation [14].

1.1.3 Demand Response in the Research Literature

Earlier works on demand response made significant contributions mainly to the area of DLC. These papers mostly posed and solved optimization problems related to DLC with varying objective functions and constraints.

In [15], a scheduling algorithm is proposed to reduce load whenever utilities experience generation shortage. This work does not attempt to minimize peak loads. A recursive dynamic programming method is used in solving the optimization problem. In [16], scheduling for air conditioner loads is proposed in order to minimize peak demands and maximize production cost savings. Predictive load modeling and energy payback calculations using stochastic methods are used as inputs to the problem. Constraints such as adding a cap on the maximum controllable loads are included in order to preserve "fairness". Multi pass dynamic programming is used to solve the optimization problem. [17] is another work by the same authors that focuses on scheduling residential air conditioners. [19] proposes scheduling to minimize fuel cost. In addition to air conditioners, scheduling of other loads such as electric water heaters has also been studied in works such as [18].

Findings and proposals in these studies are not implemented widely in practice due to many limitations. Firstly, these proposals are made for very specific scenarios. There is limited flexibility in adding more constraints and objective functions. Next, many constraints added to the optimization problems are based on predictive models. These models may not be universally applicable to all settings. In addition to this, factors such as user comfort and fairness are not quantified in a concrete manner. Also, in a realistic scenario, the number of entities participating in a DLC scheme can be high. The computational cost of solving an optimization problem in this case can be high due to the centralized nature of solutions to these problems. It becomes questionable whether it is possible to solve these optimization problems in a scale of minutes to take into account the dynamic changes in demands. Finally, implementing DLC requires extensive infrastructure changes. Controllers with bi-directional communications will have to be added to individual loads. Communication and implementation overhead can become inscalable especially in the residential sector.

More recent studies propose algorithms that build upon foundational DLC methods introduced in earlier works. Many aspects of the power grid have or are in the verge of changing. Power grid has experienced minor changes over a period of 100 years. According to [21], Thomas Edison (an early pioneer of the grid) will be familiar with the late 20^{th} century grid. Recently new components and devices have been integrated into the grid which have been described by [20]. These components include renewable energy sources (wind and solar) along with added intelligence in the home and distribution centers. These components combined with the traditional grid make a *smart grid*. Work in [22] suggests a global and local controller. The controllers will schedule appliances based on global and local heuristics. New types of appliances such as MicroCHP have been included in the control mix. Local controllers located in homes can choose to ignore these signals based on the solution to a local linear programming optimization problem. [23] suggests a control scheme for an AC/DC grid that contains controllable loads such as water heaters and electric vehicles along with variable power generators such as wind generator. [24] proposes an intelligent *demand management system* (DSM). This work uses a data warehouse to gather data using data mining and online analysis techniques to compute decisions for DSM.

The contributions outlined above have introduced newer methods to formulate and solve optimization problems with added constraints from the recent additions to the grid. Since complex computations from having to solve large optimization problems and inscalability for practical scenarios still persist, proposals in these works are no better than those in earlier works.

1.1.4 Next Steps

Solutions for DR need to have the following attributes in order to be practically implementable:

- Should be flexible. The scheme should be able to serve multiple end goals such as reducing the impact on the grid when resources are scarce, reducing fuel costs, reducing carbon footprint and increasing savings on the consumer end.
- Should not be computationally complex. The scheme should be implementable in a real-time manner, even at the scale of seconds.
- Should take into account consumer satisfaction. Noticeable discomfort should not be introduced to the end-users.
- Should not introduce any instability in the grid.

The aforementioned proposals do not satisfy all of the above requirements. In this thesis, a demand response scheme that takes into account all these requirements will be proposed.

Chapter 2

Appliances

Appliances have been common fixtures in households of Canada, United States and Europe ever since the late 19^{th} century. *Electrification* began slightly before that period. Electrification refers to the process of installing infrastructure such as generation plants, transmission lines and distribution centers necessary to allow more accessibility to electricity for consumers in that region.

Appliances are typically used to facilitate tasks such as heating a medium, moving objects, storing energy, displaying information and performing computations. Most appliances rely on electricity to enable these tasks while others use natural gas.

The overall power demand from domestic appliances in a region depends on factors such as local energy policies, appliance penetration rates, consumer usage patterns and climate. Accessibility to generation resources will dictate the energy policy in that region. Economic prosperity of the region can influence consumers' behavior and appliance penetration rates. Climate in that region depends on its geographical location.

In this chapter a holistic and detailed presentation of appliance properties will be made. A novel feature of appliances called elasticity that will aid in peak demand reductions will be introduced here as well. Then a case study of appliance properties in four regions will be discussed in order to illustrate how vastly properties of appliances and their contribution to peak aggregate demands can differ due to cultural, economic and geographical considerations.

2.1 Main Components in Electric Appliances

There are four main components in electric appliances in general. These are:

- purely resistive components
- motors
- electronic components
- energy storage components

These will be discussed at length next.

2.1.1 Purely Resistive Components

Purely resistive components convert electricity into light or heat. Electric space heaters, electric water heaters and incandescent lights are examples of appliances that use purely resistive components. Reducing the power supplied to these components will reduce the amount of light or heat emitted in direct proportion. For example, reducing power supplied to a light bulb will result in the dimming of light due to reduced radiation from the resistive coils. If the power supply is increased to more than the nominal level, damage can be incurred by the components due to wear caused by excessive heating.

2.1.2 Motor

Motors are typically used in electromechanical systems that convert electricity into torque force. This torque can cause displacement or movement. Motors are sensitive to power fluctuations as these can cause ringing effects in the motor. Excessive ringing can damage the motor.

2.1.3 Electronic Components

Electronic components are typically are used in displays and circuits. These components have nominal power requirements. Sudden reductions in power supply can cause loss of information and too much power supply can cause severe damage.

2.1.4 Energy Storage Components

Energy storage components store electricity. These are commonly found in rechargeable batteries in laptop adapters and electric vehicles. Batteries in electric vehicles can be charged with different levels of power input. Lower the charging power, the longer will be the time required to complete the charge cycle.

2.2 Elasticity

From the above discussion of the four main components, it is evident that resistive and energy storage components are tolerant to reduction of power supply from the nominal level whereas motor and electronic components are not so lenient.

Since the resistive and energy storage components are flexible and will not incur any damages due to variation of power supply within a certain threshold, these components will be referred to as *elastic* components.

When power supplied to elastic components is varied, the duration required to complete its activity will also be increased in inverse proportion. For example, if the power supplied to the heating coil in a water heater is reduced by half, then the time required to complete its operation of heating the water up to the desired temperature will double. In order to validate the above statements for resistive heating elements, one simplifying assumption is necessary. It will be assumed that the purely resistive components function in a completely insulated space so that no heat will be lost to the ambient environment.

2.3 Properties of Appliances

The Smart-A report lists the following as common household appliances [13]:

- Washing Machine (WM)
- Tumble dryer (TD)
- Dishwasher (DW)
- Oven (O)
- Stove (S)

- Refrigerator (R)
- Room Air Conditioner (AC)
- Electric Water Heater (EWH)
- Electric Space Heater (ESH)

Plug-in Hybrid Vehicles are not included in this list as these have not yet noticeably infiltrated the market yet.

Before providing a detailed overview on the properties of appliances, notations that will be used in the remainder of this document will be introduced next.

2.3.1 Notations and Functions

Let j represent an appliance entity. $AppType(j)$ will return a value from the set {WM, TD, DW, O, S, R, AC, EWH, ESH} containing all the appliances introduced earlier. This function can be used to identify what appliance j is. $Region(j)$ will return the region that j resides in from the set O, Q, I, F representing Ontario, Quebec, India and France.

It is assumed that appliances have a *nominal* operating cycle in which appliances operate using a series of constant *power phases*. Phases in which elastic components are active will be referred to as *elastic phases*. The trajectory depicting the power consumption of an appliance when it is active will be referred to as the *load profile*.

The power consumption profile of appliances can be deterministic or non-deterministic. For instance, appliances such as dishwashers, washing machines and dryers have fixed modes of operation for which it is possible to know beforehand the duration required to complete operation and the amount of power consumed during that interval. These appliances have *deterministic load profiles*. Other appliances such as fridge and air conditioners work to maintain the temperature of an environment close to a preset value. Uncontrollable external factors such as weather dictate the appliances activity levels. These appliances have *non-deterministic load profiles*.

The load profile of appliances of the same type can vary across regions. For example, in some places, appliances can use electricity for heating while others can use gas instead.It is assumed that the load profile of appliance type k is the same within a region. The total duration of operation of an appliance during a nominal cycle is $\Delta(k, r)$. When the appliance is at phase l, it will require $\delta(l, k, r)$ for phase l to complete. The typical power drawn during phase l is $P(l,k,r)$. The typical time that phase l starts after the beginning of operation of appliance k in region r is $t(l,k,r)$. The total number of elastic and inelastic phases during a nominal operating cycle of an appliance of type k, in region r is $m(k,r)$. $\phi(l,k,r) = 1$ when phase l of appliance type k in region r is elastic and is 0 otherwise. The penetration rate of appliance type k can be differ across regions. $pr(k,r)$ returns the percentage of appliances in region r that are of type k.

The activity patterns of appliances can be classified in three broad categories. Appliance can operate *once* a day ($Class(k) = 1$), in a *cyclic* ($Class(k) = 2$) manner or *a-cyclically* ($Class(k) = 3$). Examples of appliances that operate once a day are washing machines and dryers. Appliances that are active in a relatively cyclic manner are ACs and refrigerators. Acyclic appliances include water heaters that are active more than once a day but not in a periodic manner.

In the following sections, a description of the aforementioned appliances is provided.

2.3.2 Washing Machine

A washing machine contains two main components - a tub and a drum. Water is heated to temperatures ranging from 30 to 90 $°C$ either with electricity or gas. An induction motor is used to spin the drum at high speeds for the rinse and wash cycles.

Figure 2.1 contains the average load profile of a typical washing machine in France. This washing machine uses a local electric heater to heat water. The highest consumption of power occurs during the water heating period. The power consumption from the motor is only a fraction of that required for water heating.

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of ($\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r)$)
WM	O	1	85	[(0, 500W,30min)]
	Q	1	90	[(1, 2000W, 15min), (0, 950W,15min), (0, 0W, 30min), (0,300W,15min)]
	F	1	95	[(1, 2000W, 15min), (0, 0W, 30min), (0, 300W,15min)]
	I	1	95	[(0, 700W,30min)]

Table 2.1: Properties of Washing Machine

Table 2.1 lists the properties of washing machines in four regions. Washing machines in Ontario and India typically use gas to heat water and only consume power for spinning

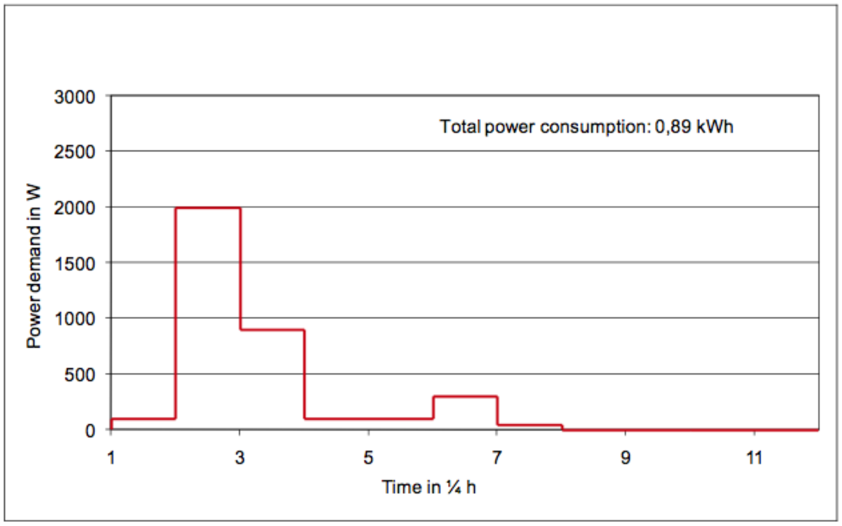

Figure 2.1: Average Washer Load Profile Curve [13]

the drum. Washing machines in Quebec and France use local resistive components for heating water. The penetration rates of washing machines in all four regions are very high. Washing machines using purely resistive heating elements can be classified as elastic.

2.4 Tumble Dryer

A tumble dryer consists of a drum, fan and a heating element. The heating element powered by either gas or electricity is used to heat the air which is then blown over the wet clothes by the fan. The drum spins during the operation of the dryer in order to maximize the exposure of clothes to the heater air. The drum and the fan are spun with an induction motor.

Figure 2.2 illustrates the load profile of a dryer in France. The heating element is electric and is active throughout the operating cycle of the dryer. The heating intensity is reduced in steps during the operation period of the dryer.

Table 2.2 lists the properties of dryers in Ontario, Quebec and France. The properties of dryers in India is not listed in Table 2.2 as the penetration rate of dryers is very low in this region and it is assumed that the clothes are air dried due to the tropical climate in this area. The penetration rate of dryers is around a third of households in the three regions.

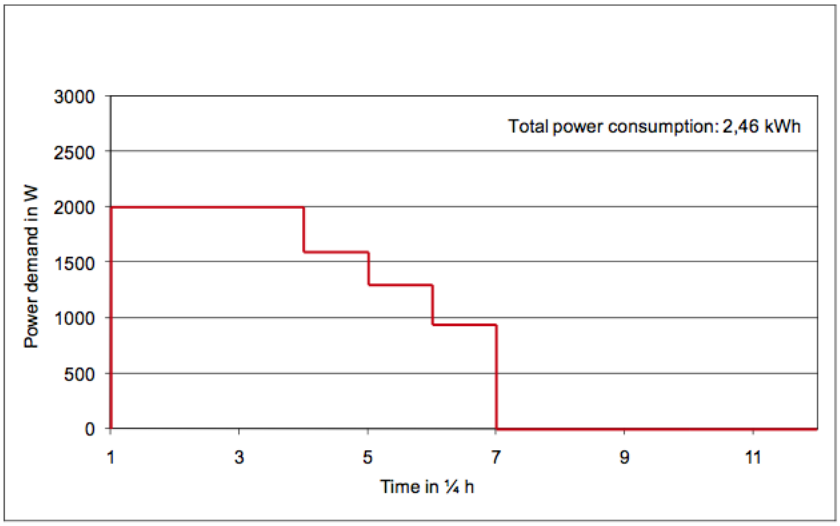

Figure 2.2: Average Tumble Dryer Load Profile Curve [13]

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of $(\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r))$
D	O	1	35	[(1, 3000W, 45min)]]
	Q	1	29	[(1, 2200W, 45min)]
	F	1	34	[(1, 2000W, 45min), (1, 1550W, 15min), (1, 1300W, 15min), (1, 950W, 15min)]

Table 2.2: Properties of Dryers

Load profiles of dryers show high power consumption for almost the entire operation cycle. This can be attributed to the use of purely resistive components for heating air. All operational phases of dryers are elastic.

2.5 Dishwasher

Dishwashers contain a basket, rotating water sprays, air and water heating chambers. Dishes are stacked in the basket. Water is heated to temperatures ranging from 50 to 70 °C. At the end of the washing cycle, hot air is passed over the dishes for drying.

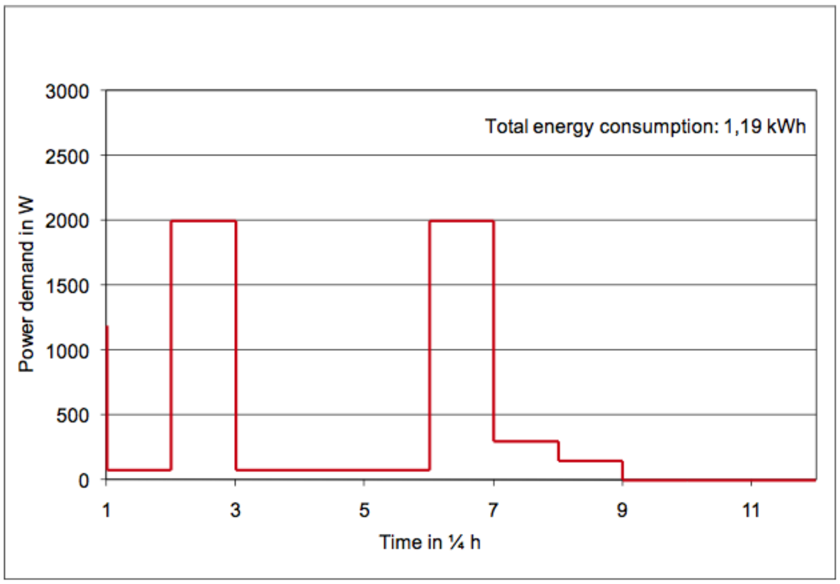

Figure 2.3: Average Dishwasher Load Profile Curve [13]

Figure 2.3 illustrates the load profile of a dishwasher used in France. There are two phases that consume high power. These correspond to the water/air heating periods during which resistive heating elements are engaged.

Table 2.3 lists the properties of dishwashers in France. Load profiles of dishwashers in Ontario have low power consumption throughout the operation cycle. Gas is used primarily to heat water and air in the region. Dishwashers in other regions predominantly use resistive components for heating. India is not included here as dishwashers are not

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of ($\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r)$)
DW	O	1	60	[(0, 50W, 15min), (0, 500W, 15min), (0, 250W, 5min), (0, 125W, 5min)]
	Q	1	55	[(0, 50W, 15min), (1, 2000W, 15min), (0, 50W, 45min), (1, 2000W, 15min), (0, 250W, 15min), (0, 125W, 15min)]
	F	1	50	[(0, 50W, 15min), (1, 2000W, 15min), (0, 50W, 45min), (1, 2000W, 15min), (0, 250W, 15min), (0, 125W, 15min)]

Table 2.3: Properties of Dishwashers

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of ($\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r)$)
S	F	1	58.4	[(1, 1500W, 3min), (0, 0W, 2min), repeat for 7 cycles: (1, 1500W, 1min), (0, 0W, 1min)]

Table 2.4: Properties of Stove

commonly used in Indian households. Phases during which purely resistive components are engaged will be referred to as elastic.

2.6 Stove

Stoves can either use gas or electricity. For stoves with electric hobs, the range switches on and off to maintain the heat setting selected. An example of the load profile of an electric stove that can be found in France is illustrated in Figure 2.4.

Table 2.4 lists the property of stoves in France. In all other regions electric stoves are not used predominantly and hence not included in Table 2.4. All phases in the load profile of this stove are elastic as electric range is used.

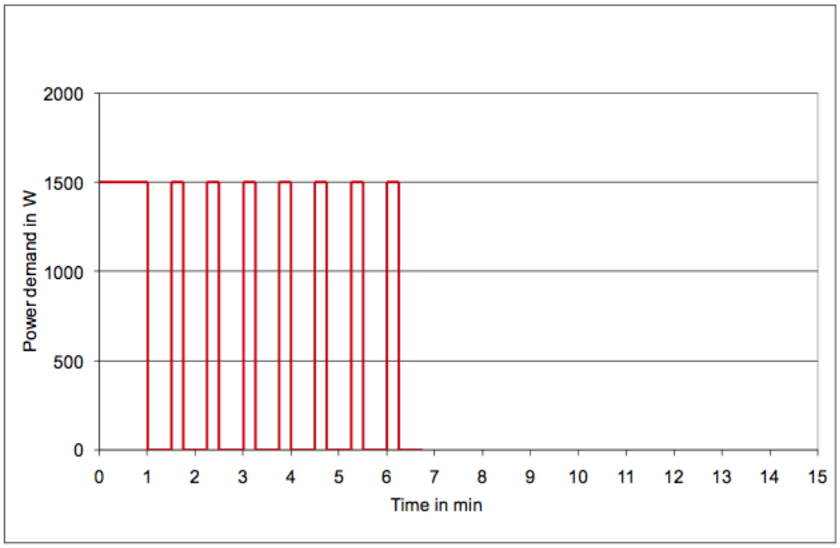

Figure 2.4: Average Stove Load Profile Curve [13]

2.7 Oven

Electric oven operates in a similar manner as the stoves. The heating coil periodically turns on and off to maintain the temperature within the oven. Figure 2.5 illustrates the load profile of an electric oven in France. The oven activates the resistive coil for an extended period at the beginning of the oven's operation. Then the range switches on and off periodically to maintain the temperature initially attained in the oven.

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of $(\phi(l,k,r),\ p(l,k,r),\ \delta(l,k,r))$
S	F	1	97	[(1, 600W, 20min), repeat for 8 cycles: (1, 600W, 3min), (0, 0W, 2min)]

Table 2.5: Properties of Oven

Table 2.5 lists the properties of an oven in France. All phases of the load profile of electric ovens are elastic. In all other regions, electric ovens are not used predominantly and hence not included in Table 2.4.

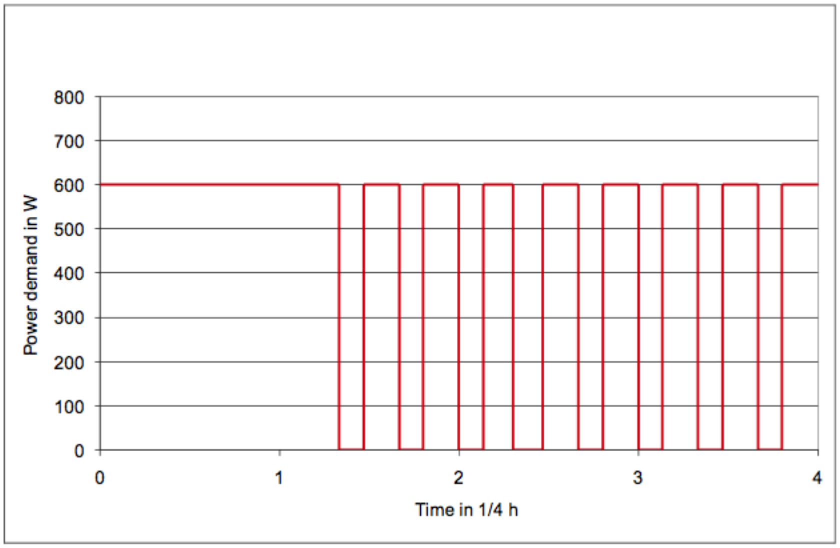

Figure 2.5: Average Oven Load Profile Curve [13]

2.8 Refrigerator

The refrigerator contains refrigerant which aids with the cooling process. The refrigerant is in its gaseous form at temperatures as low as -27 °C. The compressor in the refrigerator compresses the refrigerant into liquid form. The pressurized liquid refrigerant is then passed through the coils within the fridge. The liquid absorbs the heat within the fridge and returns to its gaseous form. This cycle repeats in order to maintain the temperature setpoint within the fridge. This temperature is typically maintained between 4 to 6 °C. The compressor uses an inductive motor. The active periods of the refrigerator during the day depends on the number of times its door is opened and the amount of food loaded into it. The compressor in the fridge cannot have a 100% duty cycle. The thermal energy dissipated by the compressor can cause damage to the internal components. Hence compressors have a limit on the maximum time they can operate continuously and a minimum duration for the period of rest after activity.

Figure 2.6 illustrates the load profile of a refrigerator in France. The correlation between the internal temperature of the fridge and the power demand is shown in this plot. When the temperature in the fridge increases up to a threshold, the compressor is activated. It is on until the temperature returns back to the setpoint.

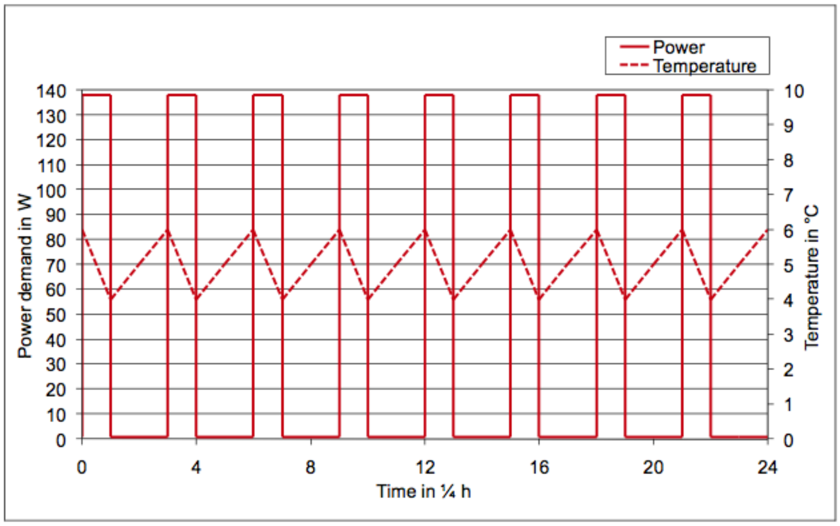

Figure 2.6: Average Refrigerator Load Profile Curve [13]

k	$Region(k)$	$Class(k)$	$pr(k, r)$ %)	Nominal load profile in tuples of ($\phi(l, k, r)$, $p(l, k, r)$, $\delta(l, k, r)$)
RF	O	2	100	[(0, 130W, 15min), (0, 0W, 15min)]
	Q	2	100	[(0, 130W, 15min), (0, 0W, 15min)]
	F	2	100	[(0, 138W, 15min), (0, 0W, 15min)]
	I	2	100	[(0, 200W, 15min), (0, 0W, 15min)]

Table 2.6: Properties of Fridge

Table 2.6 lists the properties of refrigerators in all four regions. The power consumption during active periods varies slightly across regions. Since no elastic components are active during the operational cycle, fridge is an inelastic appliance.

2.9 Room Air Conditioner

The internal workings of an air conditioner is similar to that of the refrigerator. The only difference is that the space being cooled is much larger and many more factors such as insulation in the area and external climates can affect the activity of the air conditioner.

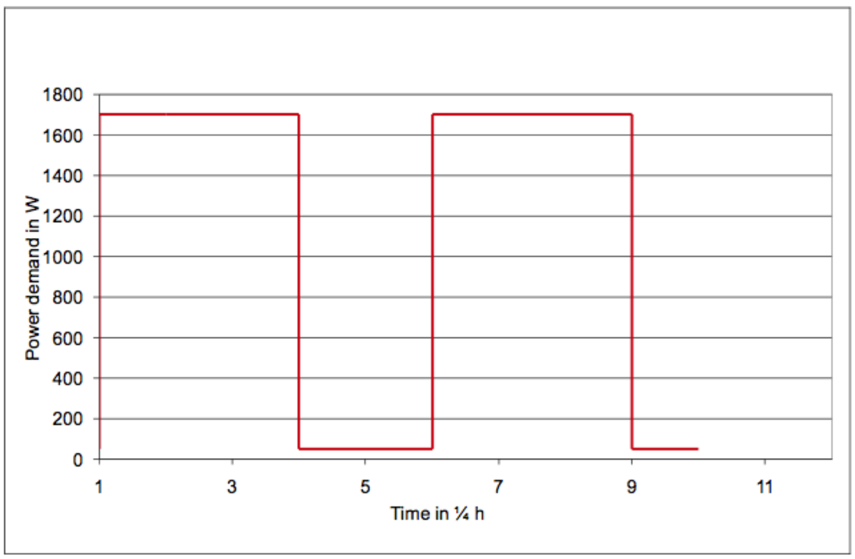

Figure 2.7: Average AC Load Profile Curve [13]

Figure 2.7 illustrates the load profile of an AC in France. The power consumption during active periods is much higher than that consumed by the refrigerator.

ACs like the fridge are inelastic appliances. Table 2.7 shows that the penetration rate of ACs is the highest in Ontario. During a hot summer day, ACs can contribute to a significant portion of aggregate peak demand. In this case, since ACs are not elastic, any schemes developed using elasticity will have to be coupled with other schemes such as using scheduling to redistribute the active periods of the ACs.

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of ($\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r)$)
AC	O	2	80	[(0, 2500W, 15min), (0, 0W, 15min)]
	Q	2	47	[(0, 2500W, 15min), (0, 0W, 15min)]
	F	2	12	[(0, 1700W, 15min), (0, 0W, 15min)]
	I	2	17	[(0, 1700W, 15min), (0, 0W, 15min)]

Table 2.7: Properties of Air Conditioners

2.10 Electric Water Heater

There are two types of electric water heaters - centralized and distributed. Centralized heaters preheat a large amount of water to a certain temperature at a certain time in the day. As the day wanes, short spikes of power consumption can be observed from the water heater. This power is drawn to maintain the temperature of water. Heat storage mechanisms such as good insulation is employed in order to reduce the frequency of reheating the water. Distributed heaters, on the other hand, use high power to heat water when in demand. The power used can range from 18 kW to 27 kW. These heaters are not commonly found in households and will not be discussed further.

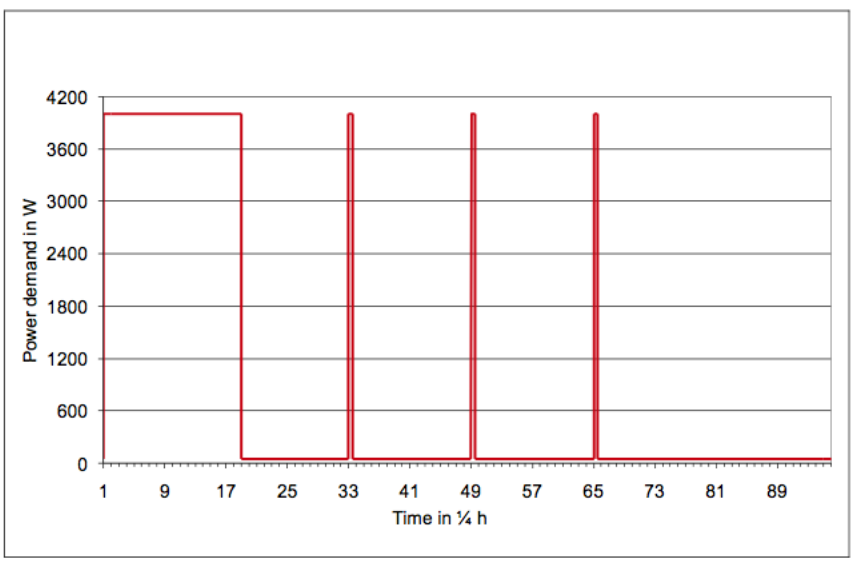

Figure 2.8: Average Electric Water Heater Load Profile Curve - 300 litres of water [13]

Figure 2.8 illustrates the load profile of a centralized electric water heater in France. This water heater consumes 4000 W of power during heating phases which is considerably lower than that used by distributed water heaters.

k	$Region(k)$	$Class(k)$	$pr(k, r)$ %)	Nominal load profile in tuples of $(\phi(l, k, r), p(l, k, r), \delta(l, k, r))$
EWH	O	3	23	[(1, 2000W, 30min)]
	Q	3	23	[(1, 2000W, 30min)]
	F	3	45	[(1, 2000W, 30min)]
	I	3	30	[(1, 2000W, 30min)]

Table 2.8: Properties of Electric Water Heater

Table 2.8 lists the properties of electric water heaters in all four regions. Since the water heater uses an elastic component for heating water, it is an elastic appliance.

2.11 Electric Space Heater

Electric space heaters like electric water heaters can either be direct or storage heaters. Direct heaters use convection to suck in cool air which is then passed through the heating elements. Since hot air is less dense, it will elevate to higher grounds allowing cooler air to replace it which will then be fed into the heater. Direct heaters will not be considered here as its penetration information is not available. Storage heater consists of an insulated tank whose core is heated up to 600 to 700 °C. A mixing valve regulates the temperature of air being blown into the space.

Figure 2.9 illustrates the load profile of a storage electric heater in France. The appliance consumes 8500W of power during active periods which typically occurs during midnight.

Table 2.9 lists the properties of electric space heaters. India is not included in this table as it is assumed that space heaters are not used due to the tropical climate in vast majority of the region. Since the electric space heater uses elastic components, it is an elastic appliance.

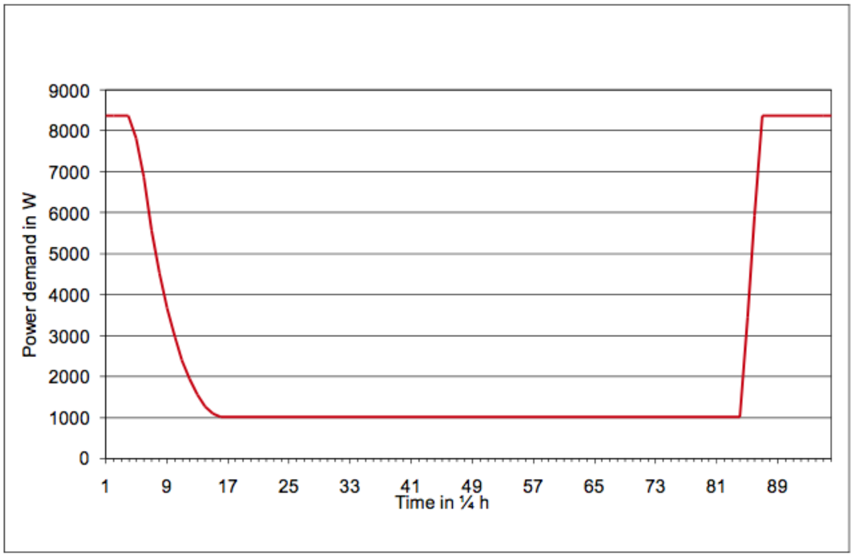

Figure 2.9: Average Electric Space Heater Load Profile Curve [13]

k	$Region(k)$	$Class(k)$	$pr(k,r)$ %)	Nominal load profile in tuples of ($\phi(l,k,r)$, $p(l,k,r)$, $\delta(l,k,r)$)
ESH	O	3	10	[(1, 8000W, 30min)]
	Q	3	58	[(1, 8000W, 30min)]
	F	3	22	[(1, 8500W, 30min)]
	I	3	30	[(1, 8000W, 30min)]

Table 2.9: Properties of Electric Water Heater

2.12 Significance of Elasticity in Appliances

From the above description of appliances, it is clear that elasticity in appliances can serve as a promising tool in demand response. The following observations on elasticity illustrate why this can be true:

- Elastic components typically have high power draw in comparison to inelastic components.
- Elastic components are present in most appliances and are active for a major fraction of the appliance operation cycle

Elastic components are able to reduce power draw instantaneously with no impact on the lifetime of the components or appliances. Since these components are prevalent in appliances and are major power consumers, being able to reduce their power draw when necessary is an asset in demand response schemes.

Chapter 3

Preliminary Analysis of Impact of Appliance Elasticity on Peak Aggregate Demands

In this chapter, the potential for peak demand reduction when using elasticity in appliances will be investigated.

Before proceeding further into the analyses, a few assumptions will have to be made. Firstly, it is assumed that it is possible to alter appliances so that their elastic components can vary power consumption when needed. Secondly, as mentioned in the previous chapter, it is assumed that the elastic components involved in heating processes are located in well insulated environment. This leads to the next assumption which is if the power consumed by an elastic component is reduced by β then the operation duration of the component will be extended in inverse proportion and this will cause no damage to any components in the appliance. Finally, inelastic components should be able to coordinate their operations with elastic components. For example if a washing machine spins its drum using an induction motor at the same time as the elastic component is heating the water, then if the operation duration of the elastic component is extended, then the induction motor should either continue to spin the drum for the extended period or stop and wait for the heating process to complete. Any of the two actions will not cause an impact on the load profile of the appliance as the power consumed by inelastic components are almost negligible.

3.1 Comfort and Delay Budget

A demand response scheme based on elasticity will require appliances with elastic components to reduce power consumption when required. According to the assumptions stated earlier, this will result in extending the duration of appliance operation. Over-extension of operation duration may not be desirable for most consumers and can result in extreme discomfort. In order to preserve the notion of comfort for participants of DR schemes that are based on elasticity, it is necessary to define a variable called *delay budget* ($b(\alpha, k, r)$), which is the maximum time by which the nominal operation period of the appliance can be extended. α is the factor by which the operation duration of the appliance is extended. Equation 3.1 relates α with delay budget.

$$b(\alpha, k, r) = (\alpha - 1) * \delta(k, r) \tag{3.1}$$

3.2 Estimating the Potential of Appliance Elasticity

In order to estimate the potential of appliance elasticity, two scenarios need to be compared. In the first scenario, the peak aggregate demand ($pL_R(r)$) that occurs when appliances function regularly in region r will be estimated. In the second scenario, the peak aggregate demand ($pL_M(r)$) that occurs in region r when elasticity is used will be estimated. Peak aggregate demand is defined here as the highest aggregate power demand that occurs at least 0.01% of the time. The percentage peak reduction, R, is defined as:

$$R = \frac{pL_R(r) - pL_M(r)}{pL_R(r)} \tag{3.2}$$

Since in this chapter, the *potential* for peak reduction is to be estimated, a simple power consumption scheme for elastic appliances will be used for the second scenario. This scheme is discussed next.

3.2.1 Simple Power Consumption Scheme

The power consumption scheme proposed in this section changes the load profile of elastic appliances so that the power consumption by elastic components is minimized within the constraints of the allocated delay and energy constraints. The delay budget ensures that the participants' comfort is preserved and the energy constraints ensure that the elastic component is able to complete its task. The power consumption scheme is defined as the optimization problem $P_0(\alpha, r)$ listed below. The solution to this problem will vary according to the region being analyzed and it is assumed that the duration extension factor α is the same for all appliances in a region.

$$\mathbf{P_0}(\alpha, r): \quad \min_{\{\delta'(\ell,k,r)\},\{P'(\ell,k,r)\}} X$$

$$\text{s.t} \quad e(\ell,k,r)P'(\ell,k,r) \le X \ , \quad \forall \ell, k \tag{3.3a}$$

$$P(\ell,k,r) \ge P'(l,k,r) \ge 0 \ , \quad \forall \ell, k \tag{3.3b}$$

$$\delta(\ell,k,r) \le \delta'(\ell,k,r) \ , \quad \forall \ell, k \tag{3.3c}$$

$$\alpha\Delta(k,r) \ge \sum_{\ell=1}^{m(k,r)} e(\ell,k,r)\frac{P(\ell,k,r)}{P'(\ell,k,r)}\delta(l,k,r) \ , \quad \forall k \tag{3.3d}$$

$$\delta(\ell,k,r)P(\ell,k,r) = \delta'(\ell,k,r)P'(\ell,k,r) \ , \quad \forall \ell, k \tag{3.3e}$$

where $P'(\ell,k,r)$ is the new power consumption of appliance when phase l is active. $\delta'(\ell,k,r)$ is the extended time taken to complete phase ℓ. Equation 3.3d is the time constraint imposed by α. Equation 3.3e is the energy constraint that ensures that the energy consumed by the elastic component using the new scheme is the same as that consumed when the component operates regularly.

When $P'(\ell,k,r)$ is replaced by $\frac{\delta(\ell,k,r)P(\ell,k,r)}{\delta'(\ell,k,r)}$ and X by $\frac{1}{Y}$, $P_0(\alpha,r)$ can be transformed into a linear optimization problem $P_1(\alpha,r)$. This transformed problem can be solved more easily.

$$\mathbf{P_1}(\alpha, r): \quad \max_{\{\delta'(\ell,k,r)\}} Y$$

$$\text{s.t} \quad e(\ell,k,r)P(\ell,k,r)\delta(\ell,k,r)Y \le \delta'(\ell,k,r) \ , \quad \forall \ell, k \tag{3.4a}$$

$$\delta(\ell,k,r) \le \delta'(\ell,k,r) \ , \quad \forall \ell, k \tag{3.4b}$$

$$\alpha\Delta(k,r) \ge \sum_{\ell=1}^{m(k,r)} e(\ell,k,r)\delta'(\ell,k.r) \ , \quad \forall k \tag{3.4c}$$

3.3 Evaluation Methods

Now that the power consumption scheme of elastic appliances is defined, the next step is to define the methods that will be used to estimate the gains from elasticity. Monte carlo simulations and analytical derivation are the two methods that will be used for this purpose.

Monte carlo method in general relies on repeated random sampling to obtain results. It is simpler to implement. Analytical derivation of the probability of peak aggregate demands is precise however it can get computationally intractable in an exponential manner as the number of appliances increases. Hence, the results from the monte carlo method is first verified with the analytical quantification for a simple scenario in order to ensure that the estimations from the simulations are close to the analytical results. Then, the monte carlo method is used to estimate the gains of peak reduction for larger and more complex settings.

In the following two sections, the monte carlo method and analytical quantification used in this work are presented.

3.4 Monte Carlo Method

The monte carlo simulation is used to compute an estimate of the probability of various aggregate demands that can occur in a region r.

In order to do this, first the start times of appliances are simulated. The number of appliances in a region r is based on $pr(k, r)$ which is the penetration rate of appliance k in region r. The start time generation relies upon the probability distribution of the start time of that appliance over a day. An example of this distribution for a washing machine in France can be found in Figure 3.1.

Then, based on these start times, the aggregate power consumption of appliances are summed for each minute of the day. k buckets are then created. Each bucket represents a range of power. For example if the highest aggregate power is P, then bucket 1 will represent powers in the range of 0 to $\frac{P}{k}$. The k^{th} bucket represents $[P - \frac{P}{k}, P]$. Counters will be associated with each bucket. The aggregate demand in the region from the simulations at time $t_n \in [0, 1440]$ is obtained. For every increment of t_n, the counter associated with the bucket in which the aggregate power at t_n falls will be incremented. All counters are then divided by 1440.

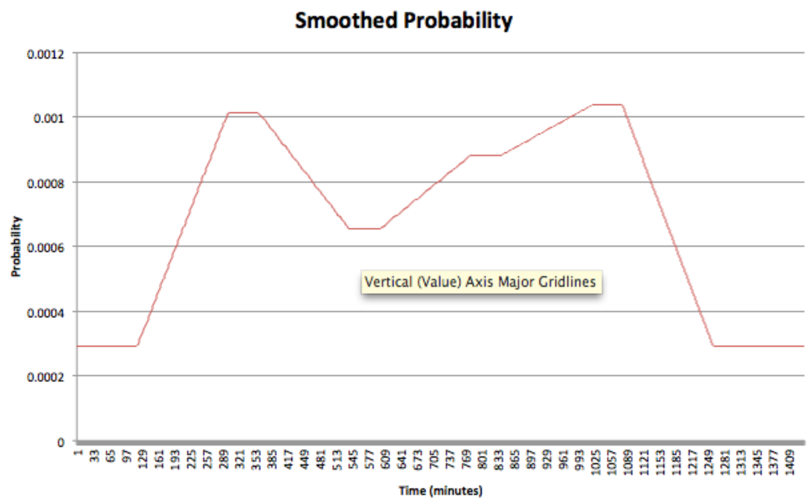

Figure 3.1: Probability of being on once in a day [13]

This is repeated *iter* number of times. The frequency of every aggregate power demand is added across the *iter* simulations and divided by *iter*. The confidence interval of the probabilities are computed across these repetitions. Large number of iterations will enable these values to converge to the statistical probabilities. Hence, *iter* is set to a large value. The monte carlo simulation is repeated for the two scenarios mentioned above. In the first, regular load profiles are used. For the second scenario, load profiles of appliances are modified according to the scheme discussed in Section 3.2.1 and the start time of appliances are kept the same as the first scenario.

The monte carlo simulation is simpler to implement and is not too computationally intense. One possible problem with this method is that the probabilities obtained may not be accurate. In order to confirm whether the results from the monte carlo simulation is close to the 'actual' value, results from the monte carlo simulations will be compared to the results from an analytical derivation of the probabilities discussed in the next section.

3.5 Analytical Derivation

In this section, an analytical computation of the probability distribution of demands from appliances in a neighbourhood of N homes is derived.

In order to simplify the derivation, it is assumed that the neighbourhood contains N homes and each home has only one appliance which is the washing machine. All statistics and properties will be based on that of washing machines in France. The load profile of the washing machine is illustrated in Figure 3.2. Figure 3.1 shows the probability of the washing machine being on during the day. It is assumed that the washing machine will be on only once a day.

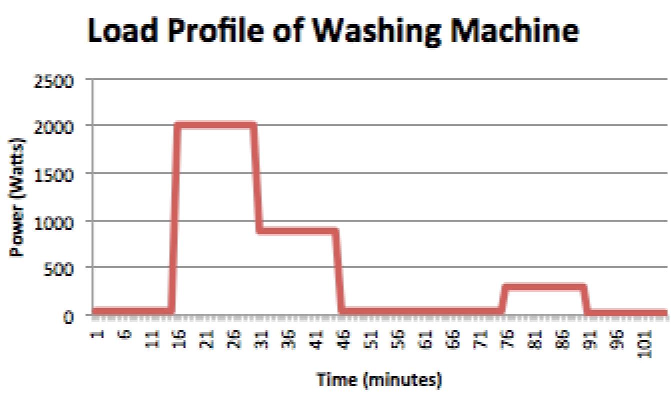

Figure 3.2: Load profile of a washing machine in France

As illustrated in Figure 3.2, washing machine can draw power in one of four power levels: 2000W, 950W, 0W, 300W. If there are N homes in a region, and suppose that the penetration rate of the appliances in the region is ignored, then there will be N washing machines in the region each drawing power at one of the four levels mentioned above at time t_n. It is assumed that the time is discretized into minutes (i.e. every increment of n is an increment of time by a minute). The probability of an appliance of type k in region r drawing a power level $P(l,k,r)$ at time t_n is listed in Equation 3.5.

$$p_{P(l,k,r)}(t_n) = \sum_{i=t_n-t(l,k,r)-\delta(l,k,r)}^{t_n-t(l,k,r)} P_{on}(i) \tag{3.5}$$

The derivation of this equation will be discussed next. Suppose the probability of a washing machine consuming 2000W at time t_n is to be computed. Phase $l = 2$ draws 2000W and it begins 15 minutes after the start time of the operation of the washing machine (i.e. $t(2, WM, F) = 15$ minutes). The duration of phase is $\delta(2, WM, F) = 15$ minutes. The probability of this appliance drawing 2000W at time t_n is equivalent to the probability of this appliance starting at any time between $[t_n - t(l,k,r)], t_n - (t(l,k,r) + \delta(l,k,r)]$. Graphically, this translates to Figure 3.3. The probability of an appliance starting at a time t_n is $P_{on}(t_n)$. Using this information, Equation 3.5 formally lists the probability of an appliance consuming $P(l,k,r)$ at time t. Since, the focus in this section is only on washing machines in France, $p_{P(l,k,r)}(t_n)$ will be referred to as $p_l(t_n)$.

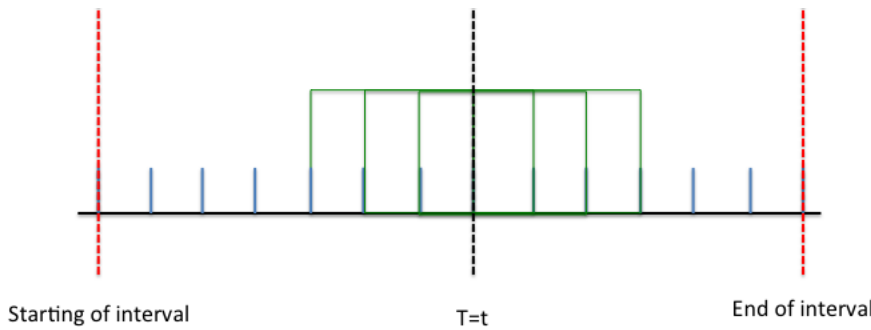

Figure 3.3: Times when a washing machine can consume 2000W at time t

Suppose i_1 washing machines are in phase 1, i_2 washing machines in phase 2, etc. Then the vector $\overrightarrow{i} = \{i_1, ..i_{m(k,r)}\}$ can be used to depict the number of appliances in their respective phases at time t_n. This vector must satisfy the following constraint: $\sum_{l=1}^{m(k,r)} i_l = N$. The probability of the vector of appliances being active in their respective phases is listed in Equation 3.6.

$$p(\overrightarrow{i}, t_n) = \prod_{j=1}^{m(k,r)} \binom{N - \sum_{1=1}^{j-1} i_l}{i_j} p_j(t_n)^{i_j} \tag{3.6}$$

The aggregate power consumed by $\overrightarrow{i}$ is listed in Equation 3.7.

$$P^N(t_n) = \sum_{l=1}^{m(k,r)} P(l,k,r) * i_l \tag{3.7}$$

The probability of obtaining an aggregate power of $P^N(t_n)$ is the summation of the probability at time t_n (Equation 3.6) of all combinations of $\overrightarrow{i}$ that will result in the value of $P^N(t_n)$. Next, the conversion of this probability into a probability mass function will be discussed.

It is known that for small Δ, the probability mass at t can be represented by $P(t-\Delta/2 \leq t \leq t+\Delta/2) = P(t) * \Delta$. In this section since time is discretized into minutes $\Delta = \frac{1}{1440}$. From these derivations, it is now possible to compute the probability of P^N occurring over a day with Equation 3.8.

$$P_{day}^{N} = \sum_{t_n=1}^{1440} P^N(t_n) * \frac{1}{1440} \tag{3.8}$$

The number of combinations of states that appliances can be at the same time is $m(k,r)^N$. Suppose $N = 100$, and there is one washing machine in each house, then the possible state that each washing machine can be in is 4 (this includes 0W when the appliance is off). Hence, the total number of non-unique aggregate demands possible over a day is 4^{100}.

This shows that even for the simplified case of only one washing machine at a home can result in an exponential growth of computation as N increases. Although this derivation can lead to a more accurate computation of probabilities, it cannot be used in a feasible manner for a larger and more complex scenario.

3.6 Comparison of Monte Carlo with Analytical Derivation

In this section, the results from both methods are compared for a very simplified scenario in which there are only two homes. Each home contains only one appliance which is the washing machine.

Matlab is used to implement the analytical computation and Monte Carlo simulations for $N = 2$ washing machines. *iter* is set to 500.

Figure 3.4(a) illustrates the results from the analytical computations. Figure 3.4(b) illustrates the results from the monte carlo method. The monte carlo simulations have been repeated 30 times and the the average of the probability distribution is calculated along with the 95% confidence intervals for each bucket. The first column in Figure 3.4(b) lists all the buckets (the buckets are not evenly divided, these values are exactly all the possible aggregate demands possible for this scenario), the second column is the probability distributions of these demands averaged over 30 repetitions and the third column lists the confidence interval. When the probability distributions from the analytical computations

0	0.93736
300	0.022108
600	0.00014786
950	0.022104
1250	0.00029324
1900	0.00014786
2000	0.022106
2300	0.00029145
2950	0.00029543
4000	0.00014786

(a) N=2, iter=500, analytical method

0	0.93913	0.00014037
300	0.01975	8.2314e-05
600	0.00011838	2.0645e-05
950	0.019976	7.7171e-05
1250	0.00023338	3.1331e-05
1900	0.00011944	1.999e-05
2000	0.020083	6.8064e-05
2300	0.00021704	2.9905e-05
2950	0.00025199	3.4791e-05
4000	0.00011958	1.9867e-05

(b) N=2, iter=500, monte carlo method

Figure 3.4: Results for analytical computations and monte carlo simulations

and monte carlo simulations are compared, it is clear that these are very close. Also the confidence intervals of the monte carlo simulations are very small. This indicates that the probability distributions obtained by the simulations are fairly stable and very close to those values obtained analytically.

3.7 Monte Carlo Results for Realistic Cases

The accuracy and consistency of results from monte carlo simulations have been confirmed in the previous section. In the following, the potential of peak demand reduction due to elasticity will be explored using monte carlo simulations for realistic cases such as neighborhoods in Ontario, Quebec, France and India. Penetration rates and load profiles used in the simulations are based on the information provided in Chapter 2.

Simulations are performed for both summer and winter seasons. It is assumed that during summer electric space heaters will not be active and during winter air conditioners will not be active with the exception of India. α is varied between $[1, 2]$ in increments of 0.1.

Figure 3.5 shows the peak demand reduction of appliances during summer. As expected, when the delay budget increases (when α increases), the peak reduction gain is higher. However, these gains plateau for higher values of α as too much extension of delay budget will not have an impact on peak demand reductions. France has noticeably high peak demand reduction for all values of α. This can be attributed mainly to the low penetration rates of air conditioners. In addition to this, France has a higher penetration of other devices such as dishwashers, washing machines, tumble dryers, ovens, stoves, electric water heaters and electric space heaters all of which have elastic components. Since the gains computed are not magnitudes and the contribution of elastic components to peak aggregate demands is high, France has the highest fraction of peak demand reduction amongst all four regions. India and Quebec are regions with the next highest peak reduction gains. India has a low penetration rate of air conditioners. The overall penetration of appliances is lower in India when compared to other regions. Since the peak reduction is a relative value, this can also explain why India has higher peak reductions that Ontario. As for Quebec, the penetration rate of air conditioners is high. Air conditioners in Quebec can contribute more significantly to peak demands than France. Finally, Ontario has the lowest relative peak reduction gains. The penetration rate of air conditioners in Ontario is the highest amongst all four region. Also, appliances like washing machine, dishwasher, oven and stove do not primarily use electricity. Hence, this may explain low peak reduction values for Ontario.

Figure 3.6 illustrates the peak demand reduction of appliances during winter. All four regions have almost similar trends of peak reduction gains during winter. A focus on the gains for $\alpha = 1.1$ will be made. Table 3.1 lists the magnitude of peak demand reduction for all four regions. Quebec, Ontario and France both have similar magnitudes of peak demand reductions. India has the lowest value. Quebec has the highest penetration of electric space heaters, followed by France and finally Ontario. Electric space heaters have a high power consumption of 8000W. Since all components in the heaters are elastic, high gains can be achieved in this case. Since most of India is a tropical region, it is assumed that no space heaters are used during winter. This may explain low peak reduction gains during winter for India.

Region	Summer	Winter
Ontario	2200W	3500W
Quebec	3000W	3950W
France	3100W	3900W
India	200W	200W

Table 3.1: Magnitude of Peak Demand Reduction for $\alpha = 1.1$ in a neighborhood with $N = 100$ homes

To put these results into perspective, an estimate of overall peak demand reduction in Quebec is made. Winter is typically the season in which peaks occur in Quebec, hence the following computations will be made for winter. In 2006, Quebec had 3.2 million

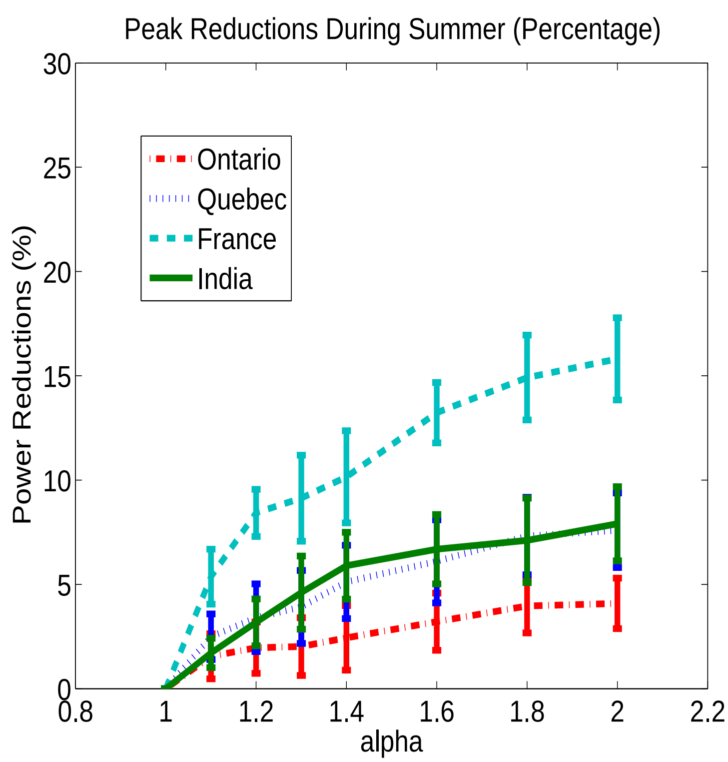

Figure 3.5: Comparison of percentage of peak reduction capacities during summer [27]

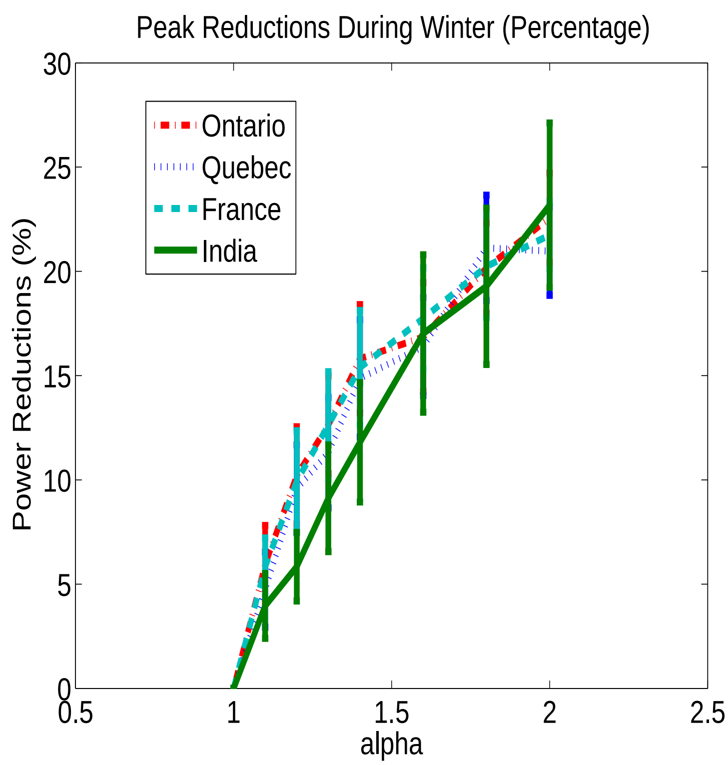

Figure 3.6: Comparison of percentage of peak reduction capacities during winter [27]

households [25]. When the simple power consumption scheme proposed in Section 3.2.1 is used on all appliances in Quebec with α set to 1.1 (10% increase in time budget), then the peak demand reduction from the residential sector can be expected to be 125 MW (3.2*3950/100). Extending the appliances operation by a mere 10 % will most likely not cause major discomfort to consumers. During summer, Quebec has a slightly lower magnitude of gains in peak power reductions. Since major contributors to peak demand during summer are air conditioners and these appliances are not elastic, it is necessary to couple elastic demand response schemes with the scheduling of air conditioners.

3.8 Conclusions from Preliminary Study

It can be concluded from the study in this chapter that elasticity has the potential for significant peak reductions. The properties of appliances vary from region to region. The amount of contribution of elastic components to peak demands depends on local appliance usage patterns, local energy policies (gas vs electricity) and climates. Although these differences exist, significant gains in peak reduction even with the simplistic scheme can be observed for all four regions studied here. Higher reduction in peak demands can be obtained with larger allocation of delay budget to appliances. A balance must be struck between discomfort caused to participants and reducing problems in the grid.

Being able to reduce peak demands can result in reducing expenditure at the scale of billions and lowering environmental impacts. These results should motivate appliance manufacturers to add controls to elastic components in appliances. Utilities should design a demand response scheme for appliances in the residential sector. Standardization of communication between appliances and utilities should be done. In the following chapter, a demand response scheme will be proposed that includes elasticity based controllers for both the appliance and utility side.

Chapter 4

Distributed Control of Elastic Appliances

In the previous chapter, the potential of elasticity in appliances was evaluated with a simple scheme in four regions. Results indicate promising potential for elasticity to address many pressing issues in today's grid. This analysis also exposed certain limitations of elasticity. In this chapter, a flexible demand response scheme based on elasticity is proposed and evaluated.

4.1 Lessons Learned from the Internet

Before delving into the details of the demand response scheme proposal, this section will present a study of congestion control protocols used in the internet. Although many differences exist between the internet and the power grid, certain parallels can also be drawn between the two. Successful features of protocols used in the internet are highlighted and how these can be incorporated into the new demand response scheme will then be discussed.

The internet has been in existence for more than two decades. The internet and the power grid are completely different entities. The internet is built on a best-effort paradigm in which entities are serviced based on the availability of resources. The power grid on the other hand guarantees reliable services. For this, utilities need to keep on expanding the infrastructure and generation resources required to cater to its ever increasing consumer base.

In the internet, there exist some protocols that have been standardized and used successfully in practice for a significant period of time. One example is the Transmission Control Protocol (TCP). TCP is designed to allow transmitting entities to infer congestion in the internet and reduce its contribution to the congestion in the internet. This protocol also ensures that the receiving entity receives all packets in order. This is a distributed protocol as only the transmitting and receiving entities exchange data between one another. A similar protocol can be applied to the power grid. Appliances can receive information from the utility about the congestion state of the grid. Then appliances can take actions necessary to reduce its contribution to congestion in the grid.

TCP has many variants. TCP Tahoe is one variant which is conservative and will be used as an example in the following. The transmitting device that uses TCP Tahoe can either be in the slow start or congestion avoidance phase. At the beginning of transmission, the device enters *slow start* phase. In this phase, the device begins transmitting data slowly. Every time the receiving entity receives a packet successfully, it sends an acknowledgement to the sender. Upon the receiving the acknowledgments, the sender doubles the data transmitted in order to utilize the capacity of the network. After the sender reaches the slow start threshold, it enters the *congestion avoidance* phase in which it starts to linearly increase data transmitted so that it does not overwhelm the network. If anytime during transmission, the sender does not receive an acknowledgement or receives duplicate acknowledgments, it halves its slow start threshold, returns to the slow start phase and drops the size of data transmitted.

Important features of this protocol that can be applied to a demand response scheme using elasticity in the power grid are the following. In the case of the power grid, the demand response scheme should minimize the contribution by appliances to congestion in the grid. Transmitters in the internet infer that the internet is in high congestion when they receive no acknowledgements from receiver. A similar method is necessary in the power grid in which the appliance is notified on a regular basis about the congestion state of the grid. With TCP Tahoe, the sender immediately drops its data transmission to minimum upon sensing congestion. Once it hits the slow start threshold, the device transmits data additively. Similarly, if worse congestion is encountered in the power grid, an appliance should minimize its impact on the grid and slowly increase its power consumption. However, if the power grid is at a 'medium' level of congestion and all appliances in elastic phases drop their power consumption to the minimum value possible, then the delay budget allocated to the appliances will be used up quickly. This will then be a waste of the delay budget. Hence, appliances need to strike a balance between reducing congestion in the network and conserving the delay budget allocated to them.

Certain lessons highlighted from successful protocols in the internet like TCP can be applied to the power grid. In the following section, design considerations of the new DR scheme will be made in light of the differences addressed in the operating paradigm of the internet and power grid.

4.2 Design Considerations

The design considerations for the new demand response scheme will be presented in this section.

4.2.1 Definition of Congestion

A demand response scheme is necessary when there is *congestion* in the grid. Congestion is a loose term that will be used to define times during which the utility is attempting to conserve or save something. This can include minimizing carbon footprint, saving generation fuel costs, reducing transformer size, decorrelating loads, saving infrastructure costs, buying time for the grid to engage its spinning reserves, taking precautions ahead of technical issues anticipated in the grid and maximizing profits. The appliances should be indifferent to the types of congestion in the grid and respond in a manner to reduce the congestion - whatever the congestion might be. Hence, the actions taken by the end systems must be independent of the cause for those actions.

4.2.2 Controlled and Controlling Entity

Utility can attempt to eliminate grid congestion at various levels which include individual homes, neighborhoods and generation source. At the level of home, congestion may occur when the power consumption of the appliances in the home exceeds the threshold set on the home by the utility. At the next level, neighborhoods typically contain about 100 homes. The area served by a local distribution substation can constitute a neighborhood. Congestions in the grid at this level can be caused by factors such as local weather conditions or loss of local generation sources. At a more global level, utilities can control multiple neighborhoods and load balance the aggregate power consumption between the neighborhoods. The scheme introduced in this work should be applicable at any level mentioned above.

The controlled entities by the utility can include individual appliances, homes and neighborhoods. Controllers placed at the level of home can control individual appliances in the home. The controller can have a high level view of which appliance is more important and allocate power appropriately. However, the home controller would have to keep an account of the types of components active and energy, power and time constraints in every appliance in that home. This can be cumbersome for a home controller. In the proposed demand response scheme, each elastic appliance will have a controller that will decide the appropriate power the appliance should draw.

4.2.3 Centralized vs Distributed Actions

In the demand response scheme, either the utility can force an end system to taken an action or the end system can respond to various states of the grid. The first case is similar to DLC. DLC is a centralized scheme in which the utility solves a complex optimization problem and forcefully adjusts the power consumption of its participants. The first problem with this method is that the computational overhead is too high. It is not possible to respond to the congestion state of the grid in a dynamic fashion. Next, forcing participants to use a specific value for power draw can be intrusive and may result in extreme user discomfort. Gathering the definition of participant's notion of comfort is not very feasible. Hence, a centralized scheme will not be appropriate in the residential sector. Instead a distributed scheme in which appliances themselves make decisions on what power to draw will be more appropriate. This way, individual consumers can set their respective comfort levels in the form of delay budgets for each elastic appliance.

4.2.4 Inferring Congestion in the Grid

The method by which end systems will infer that the grid is congested will be discussed next. Appliances can infer this implicitly or explicitly. Appliances can make local measurements of the grid. Sudden spikes or disturbances in the power supply can suggest that there are congestion issues in the grid and the appliances can take appropriate decisions based on the severity of measurements. However, these measurement technologies are not affordable and are not too precise. Also, these measurements only serve specific grid congestions that include by lack of generation sources or failure of local transmission lines. It is not possible for appliances to infer other congestion causes such as having to minimize carbon footprint or reducing infrastructure costs. The only way appliances can be aware of such congestion is through information relayed by the utility to the appliances. Currently, for TOU schemes, consumers are made known of electricity pricing the day before. Programs such as *peaksaver* have been implemented widely in certain regions in Ontario [26].

The Toronto Hydro provides its customers with a free energy display that shows information such as the cost of electricity during an hour. This will allow consumers to modify their appliance usage behaviors according to the electricity costs set by the utility during a time instant. Utilities already relay information about the state of the grid through price signals. Utilities can extend this concept by using existing devices to relay information about the grid to elastic appliances.

4.2.5 Information in the Signals

The richness of information necessary in signals relayed by the utility will be presented here. Since the actions taken by end systems are independent of the congestion states in the grid, it is not necessary to relay specific details about the type or statistics of the congestion. *Congestion signal* will be defined to be the information relayed by the utility to the appliances. Congestion signals need to be as simple as possible. The value in the congestion signal should reflect the degree of congestion in the grid. Depending on the seriousness in the grid, the appliances will be take appropriate measures to decrease it.

4.2.6 Frequency of Signals

The frequency of information relayed by the signal is important. In order to allow appliances to dynamically respond to the state of the grid, the information about the grid will have to be dynamically presented to the appliances. Communication overheads can reach a maximum of several seconds. If the communication signals are very simplistic, then the time to transmit these signals can be ignored. Hence, signals should be transmitted from the utility every δ seconds. One example of the need for dynamic signalling is when congestion in the grid is caused by high aggregate demands. In this case, there are usually periods that have very low activity or *slack* periods in the grid. Utilities will prefer to shift demands from appliances to these slack periods. Hence, appliances should be able to follow the severity of congestion dynamically. Updating appliances every hour like TOU will not be effective here.

4.2.7 Stability of the system

A highly responsive scheme can respond to changes in the condition of the grid in a quick manner. This can however compromise the stability of the grid. The grid can become instable when the aggregate demand oscillates with extreme difference between the peaks and troughs. A less responsive scheme will allow power consumption by appliances to reach a consistent state.

4.2.8 Constraints on Appliances

Energy, power and time are the three main constraints that are imposed upon appliances.

An elastic component in an appliance completes its task in a phase only when it expends the energy required for that phase. If the elastic component consumes less energy, then the appliance will be active for less time. This is not desirable as consumer dissatisfaction is very likely to occur due to incomplete work by the appliance.

Usually reducing power consumed by a component in an appliance can reduce the congestion in the grid. Reducing too much power can result in exceeding the budget requirements of the appliance. These two are conflicting constraints. In this work, more importance will be given to preserving user constraints.

4.3 Design of Appliance Side Controller

The demand response scheme proposed here consists of an appliance side controller (ASC) and a utility side signal generator (USG). First the design of the ASC will be presented in the following.

ASCs will be present in every appliance and can modify the power consumption of various elastic components in the appliance. The ultimate goal of the ASC is to enable elastic appliances to draw power just enough to offload the grid during congestion and not waste the delay budget allocated to it. It should be independent of the type and context of the signal.

The ASC proposed here will only receive one input signal every δ seconds. The ASC should be able to infer the degree of congestion in the grid from the information passed in this signal. Concepts and tools from fuzzy logics will be used by ASC for this purpose.

4.3.1 Background on Fuzzy Logics

Fuzzy logics is used to describe objects with states that have overlapping definitions. These objects can have a degree of belongingness to each state. Traditional crisp logic is not suitable for ASCs. For example, suppose congestion in the grid is defined in the following binary manner. If aggregate power in the grid exceeds a threshold say T, then the grid is labeled congested. Otherwise, the grid is not congested. According to this definition, if the aggregate demand is $0.9999T$, the grid is not congested. This rigid definition is not appropriate in this case. It maybe more appropriate to define a 'grey' area $[T - x, T]$ in which the grid can partially belong to states congested and not congested.

The degree of an object's membership to a state s when its value is x is denoted by the membership function $\mu_s(x)$. The degree of membership is a value between $[0, 1]$. If the degree of membership is 0, then the object completely does not belong to that state. If the degree of membership is 1 then the object completely belongs to that state.

Fuzzy logics can be used to make decisions. One example of such a system is called the fuzzy inferencing system. Rules of the form IF ... THEN ... compose the fuzzy inferencing system. These rules define a certain set of actions that should be taken if the object is at a certain state. The state portion of the rules is called the antecedent and the action portion is called the consequent. A rule can have multiple objects and multiple consequences. These rules are typically defined by humans who are 'experts' in the field or from trends in the environment called the knowledge base. The final action(s) is derived by *composing* the values of the object with the rules in the fuzzy inferencing system.

4.3.2 Notations

Notations that will be used for the description of ASC will be presented next.

$S_c(t_n)$ is the congestion signal transmitted by the utility to appliances. δ is the duration within which a congestion signal is transmitted by the grid. $\phi(l, k, r)$ was introduced in Chapter 2 to indicate whether the appliance is elastic or not in phase l. Since the perspective of ASC is local, it is possible to drop k and r. $\phi(l)$ will be used instead due to convenience. $E_l(t_n)$ is the amount of energy remaining to be consumed by the appliance in order to complete phase l at time step t_n. $B_r(t_n)$ is the amount of budget remaining for the device at time step t_n. B_o is the original delay budget allocated to the device. P^l_{min} is the minimum power that can be consumed by the appliance when it is in phase l. This can be set by the manufacturer or consumer. P^l_n is the nominal power that is consumed by the appliance at phase l and this is equivalent to $P(l, k, r)$ in Chapter 2. Δ^l_n is the nominal time taken by the appliance to complete phase l and this is equivalent to $\delta(l, k, r)$ in Chapter 2. $P_m(t_n)$ is the minimum possible power the appliance can consume given the availability of delay budget. $P(t_n)$ is the power consumed by the appliance at time t_n.

4.3.3 Updating Energy

One way to ensure that elastic components have completed their task, even when their power consumption varies from the nominal power, is to keep track of their energy consumption when active. $E_l(t_n)$ is the total energy remaining to be consumed by the elastic component in phase l and is updated according to Equation 4.1. At any time t_n, $E_l(t_n)$ must be greater than or equal to 0.

$$E_l(t_{n+1}) = E_l(t_n) - P(t_n) * \delta \tag{4.1}$$

4.3.4 Updating Budget

When the appliance reduces its power consumption below the nominal power for the phase it is at, the delay budget allocated to the appliance is being used. In order to ensure that the delay budget is not exceeded by the appliance, ASC needs to update and keep track of how much delay budget remains for the appliance at time t_n. The computation of how much delay budget $B_r(t_n)$ remains in an appliance at time t_n can be computed according to Equation 4.2. At any time t_n, $B_r(t_n)$ must be greater than or equal to 0.

$$B_r(t_n) = B_r(t_{n-1}) - \delta + \frac{\delta * P(t_{n-1})}{P^l_{n-1}} \tag{4.2}$$

4.3.5 Heeding Budget Requirements

When ASC decides on the value of power to allow the appliance to draw upon receiving the congestion signal, it needs to ensure that its decision does not result in exceeding the budget requirements. For this reason, the minimum power an appliance can consume $P_m(t_n)$ at time t_n is maintained. One constraint on $P_m(t_n)$ is $P^l_{min} \leq P_m(t_n) \leq P^l_{max}$. The minimum allowable power that can be consumed by the appliance must be between the absolute minimum power (P^l_{min}) permitted for the appliance during phase l and the nominal power of the phase P^l_{max}. If $B_r(t_n) \geq \delta$ then $P_m(t_n) = P^l_{max}$ otherwise $P_m(t_n) = P^l_{min}$

4.3.6 Congestion Signal

ASC accepts one congestion signal, $S_c(t_n)$, at a time. $S_c(t_n)$ reflects the congestion state of the grid. The grid will transmit a congestion signal to all appliances every δ seconds (typically 2 seconds to reflect the communication delay) at time t_n. For ASC to be independent of the definition of congestion used by the grid, the value of the signal transmitted by the utility must be a general value. The membership functions interpreting the degree of congestion reflected by $S_c(t_n)$ are assumed to be true by all participating ASCs and is illustrated in Figure 4.1.

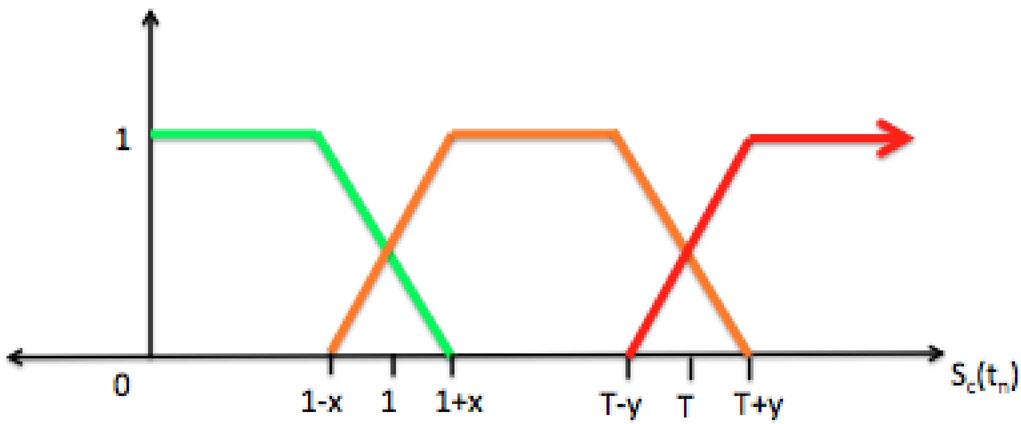

Figure 4.1: Membership function for $S_c(t_n)$

According to these membership functions, the signals have three states of severity. These are 'good', 'bad' and 'worse'. These are labels assigned to various states of congestion in the grid. According to Figure 4.1, when $S_c(t_n) < 1 - x$ then the congestion state is 'good'. If $S_c(t_n) \geq 1+x$ and $S_c(t_n) < T-y$ then congestion state is 'bad'. If $S_c(t_n) > T+y$ then congestion state is 'very bad'. When $S_c(t_n)$ takes values between these regions, then the assignment of labels becomes fuzzy and the degree of membership to each state will be partial. x, y, T are parameters.

4.3.7 ASC Design

The decision making algorithms used by ASC is designed with tools from fuzzy logics. The action of ASC is computed every time a congestion signal $S_c(t_n)$ is received by the appliance. This action is computed using a fuzzy inferencing system. The only input to this system is $S_c(t_n)$. The rules composing the fuzzy inferencing system are in effect only for appliances that are operating elastic phases at t_n. These rules are described linguistically in Table 4.1.

Rule	Description
Rule 1	If congestion is 'good' then increase power in 'small' increments (additive increase)
Rule 2	If congestion is 'bad' then decrease power in 'small' decrements (additive decrease)
Rule 3	If congestion is 'worse' then decrease power in 'large' decrements (go to minimum power possible)

Table 4.1: Rules for fuzzy inferencing system

The first part of a rule in the ruleset is the antecendent. The labels in the antecedent have been defined earlier in the membership functions in Figure 4.1. Hence, the actual membership of $S_c(t_n)$ can be evaluated from these membership functions. The later part of a rule in the ruleset represents the consequence. In this case, the consequences are $\{$*small increments, small decrements, large decrements*$\}$. These consequences are the actions that must be taken by ASC after inferring the state of the grid from the congestion signals. These rules make logical sense. Suppose, the appliance is at phase l which is elastic at time t_n. Following is a discussion of why the consequences defined in the rule set is appropriate for each state of congestion.

If the appliance is consuming power that is lower than its nominal power, P_n^l, at t_n and the grid is at a 'good' congestion state, then ASC can allow the appliance to increase its power consumption. Allowing large increase in power consumption can cause instability in the system. This is because, if all appliances react in the same manner, the aggregate power consumption will increase too rapidly. In order to prevent such instability, Rule 1 directs ASC to increase power consumption in small increments.

If the appliance is consuming power that is greater than the minimum power possible at time t_n, which is $P_m(t_n)$, and the congestion in the grid is 'bad', then the appliance should decrease its power consumption. If power is decreased in high decrements, then the delay budget remaining for the appliance will be used more rapidly. Since the state of the grid is not worse, too severe of an action is not necessary. Hence, power can be decreased in small decrements. This can also ensure that the delay budget is not used unnecessarily.

The last case in which the congestion state of the grid is worse, appliances should take a drastic action to offload the grid. Appliances should immediately drop power consumption to $P_m(t_n)$ which is the minimum power the appliance can consume while preserving budget constraints.

These consequences can be defined mathematically as follows. When the consequent is *large decrements*, the appliance should take the minimum possible power. In this case, consequent one is $C_1 = P_m(t_n)$. *Small decrements* implies that the appliance should reduce its power consumption by δW if after reduction, its power consumption is still greater than $P_m(t_n)$. This can be expressed as $C_2 = max[P_m(t_n), P(t_{n-1}) - \omega]$. ωW is a parameter. When the consequent is *small increments*, appliances can increase their power consumption by δW as long as after the increment the power consumption does not exceed the nominal power. This can be expressed as $C_3 = max[P^j, P(t_{n-1}) + \omega]$. A summary of the mapping of each consequent to its expression is listed in Table 4.2.

Consequent	Expression
Large Decrement	$C_1 = P_m(t_n)$
Small Decrement	$C_2 = max[P_m(t_n), P(t_{n-1}) - \omega]$
Small Increment	$C_3 = min[P^j, P(t_{n-1}) + \omega]$

Table 4.2: Consequences and Expressions

The congestion signal $S_c(t_n)$ can have fuzzy memberships to states 'good', 'bad' and 'worse'. The input $S_c(t_n)$ can be composed with the fuzzy inferencing system according to Equation 4.3 to obtain the final action that should be taken by the ASC.

$$P(t_n) = \frac{\mu_g(S_c(t_n)).C_1 + \mu_b(S_c(t_n)).C_2 + \mu_w(S_c(t_n)).C_3}{\mu_g(S_c(t_n)) + \mu_b(S_c(t_n)) + \mu_b(S_c(t_n))} \tag{4.3}$$

Equation 4.3 is the weighted average of the consequences computed according to Table 4.2. The weights are the membership of the congestion signal to each congestion state of the grid.

4.4 Design of Utility Side Signal Generator

In the previous section, the design of the appliance side controller was presented in detail. Next, the design of the utility side signal generator (USG) will be discussed. First, a simple signaling scheme is presented. Then based on the problems identified in the simple scheme, an enhanced version of the USG will be presented.

4.4.1 Simple USG

The ASC is independent of the utility's definition of congestion. In order to understand how an ASC can contribute to congestion in the grid and to show the importance of proper signal generation, first, a simple case will be studied. In this case, the utility generates signals $S_c(t_n)$ according to Equation 4.4.

$$S_c(t_n) = \frac{P_a(t_n)}{S} \tag{4.4}$$

where $P_a(t_n)$ is the aggregate power consumption of all appliances in the system at time t_n. S is the setpoint at which if the aggregate power demand exceeds this value, $S_c(t_n) > 1$. It is assumed that the membership functions in 4.1 representing the congestion states in the grid will be used by all ASCs in the system. Hence, according to the membership functions, when the aggregate demand reaches S, the congestion state of the grid is partially 'good' and partially 'bad'.

For the case study in this section, it will be assumed that there is only one appliance which is the dishwasher in the grid. Parameters of the ASC that includes x, y, T, δw, P^l_{min} and α are set to 0.1, 0.1, 1.2, 5W, $\frac{1}{2}P^l_n$ and 0.1 respectively. The performance metric is listed in Equation 4.5.

$$E_u(S) - E_c(S) \tag{4.5}$$

where $E_c(S)$ is the magnitude of total energy consumed by all controlled appliances when the aggregate power consumption of the appliances exceed S. Similarly $E_u(S)$ is the magnitude of total energy consumed by all uncontrolled appliances when the aggregate power consumption of the appliances exceed S. In order to illustrate the impacts of various types of signaling, three scenarios in which S is set to $600W$, $1200W$ and $1600W$ respectively are studied.

Figure 4.2 shows the load profile of a controlled versus uncontrolled dishwasher. In this case, the minimum power that can be consumed by the two elastic phases in the dishwasher is 1000W which is half of the nominal power in these phases. Since the setpoint is set to a very low value (lower than P^l_{min}), the signal generated by the ASC is always going to indicate 'worse' congestion in the grid. Upon receiving these signals, according to the fuzzy inferencing system in the ASC, the appliance will drop its power consumption to the minimum power possible. However, once the allocated budget depletes, the ASC returns the appliance to the nominal power consumed by the phase. This is done to preserve comfort requirements of the consumers. The second phase in the appliance consumes

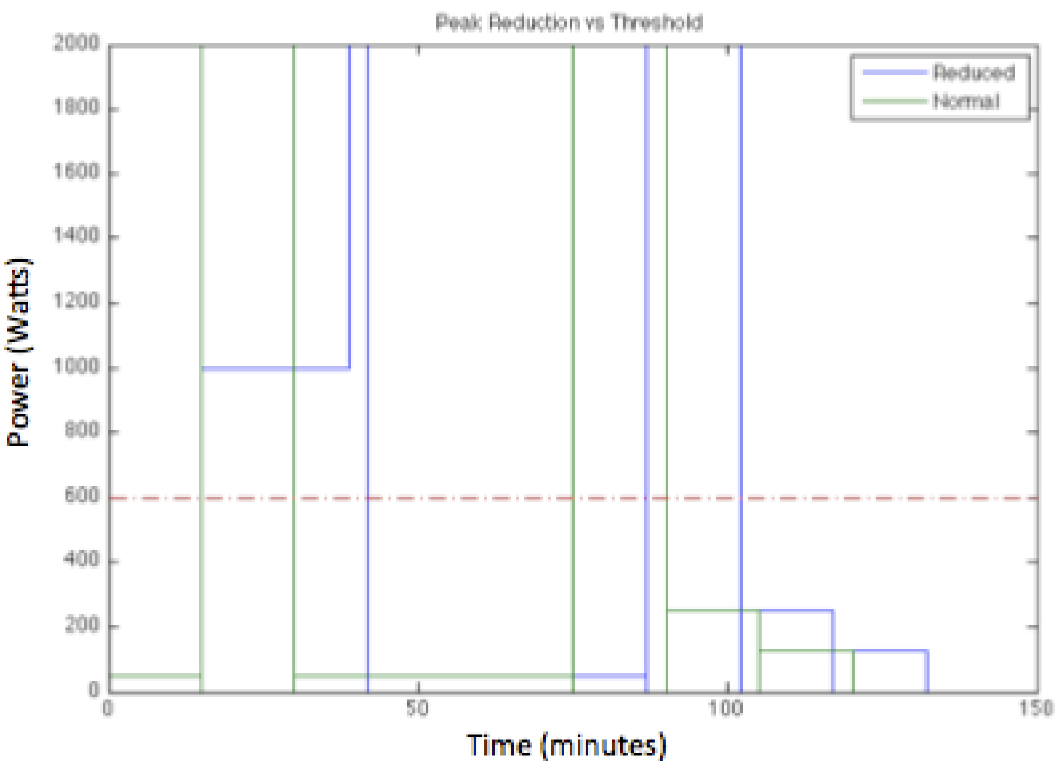

Figure 4.2: Power consumption profile for $S = 600W$

nominal power as there is no delay budget remaining for the appliance. From this example, it is clear that setting congestion signals too pessimistically can result in the ASC of an appliance to not optimally contribute to reducing congestion in the grid.

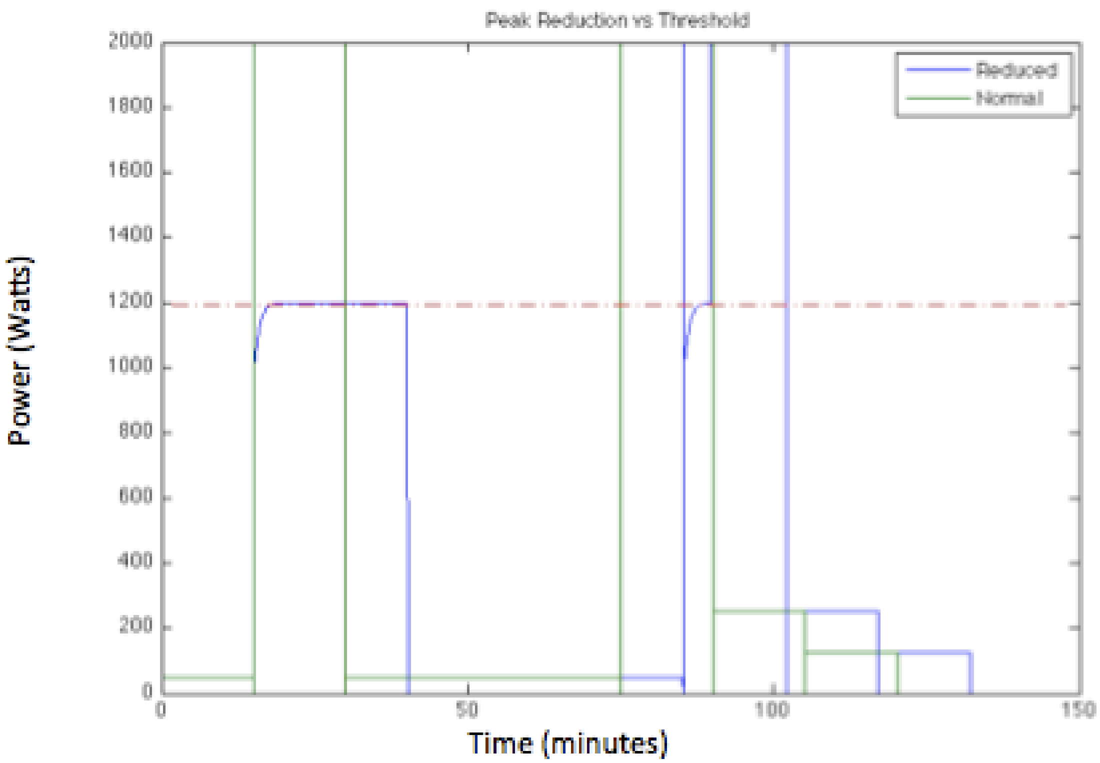

Figure 4.3: Power consumption profile for $S = 1200W$

Figure 4.3 shows the power consumption of a controlled and uncontrolled dishwasher when signaling from the grid is based on $S = 1200W$. In this case, P^l_{min} is lower than S. Hence, in the first elastic phase of the dishwasher, the ASC allows the appliance to reach the 1200W setpoint. Once the appliance finds the setpoint, the ASC remains around the setpoint until the phase completes as there is still remains adequate time budget. In the next elastic phase, the ASC allows the appliance to reach the setpoint until all of the time budget depletes. After this point, the appliance returns to its nominal power consumption. The total extension of the operation duration is 10 minutes as prescribed by the time delay. In this example, it is clear that ASC allows the appliance to find the power required to minimize congestion in the grid while delay budget remains. Once the appliance finds the appropriate power level, it remains stable (there are no oscillations). Even in this example, the congestion signal might be too severe as the appliance returns to consuming its nominal power.

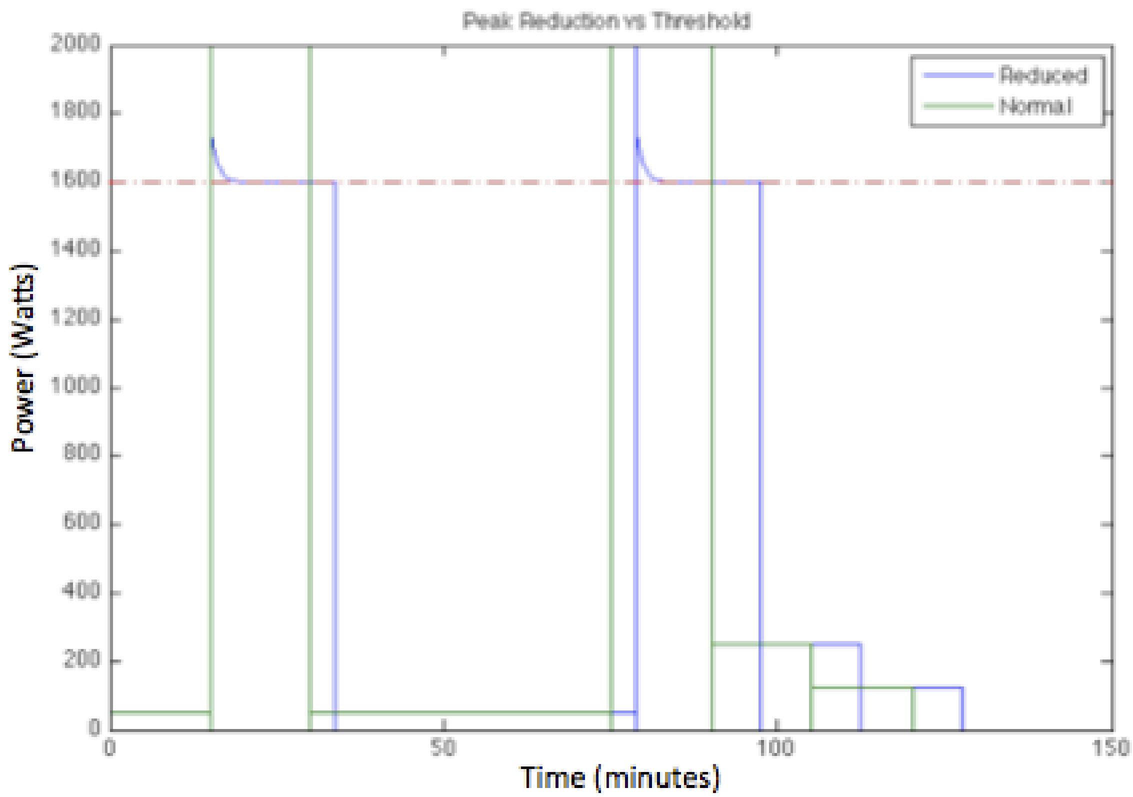

Figure 4.4: Power consumption profile for $S = 1600W$

Figure 4.4 shows the power consumption of a controlled and an uncontrolled dishwasher. In this example, the setpoint is set to 1600W. For both elastic phases in the appliance, the ASC is able to find the power consumption that will minimize the congestion in the system. The amount of energy consumed by the appliance above the setpoint is zero. These results exhibit appliance behavior that is desirable.

Next, a similar study is made at a larger scale. Monte Carlo simulations are used for this purpose. The neighborhood studied is Quebec. All appliance properties used in the simulations are as listed in Chapter 3. Figure 4.5 illustrates the results for various delay budgets used by the ASCs in all appliances in the region and for various S used by the

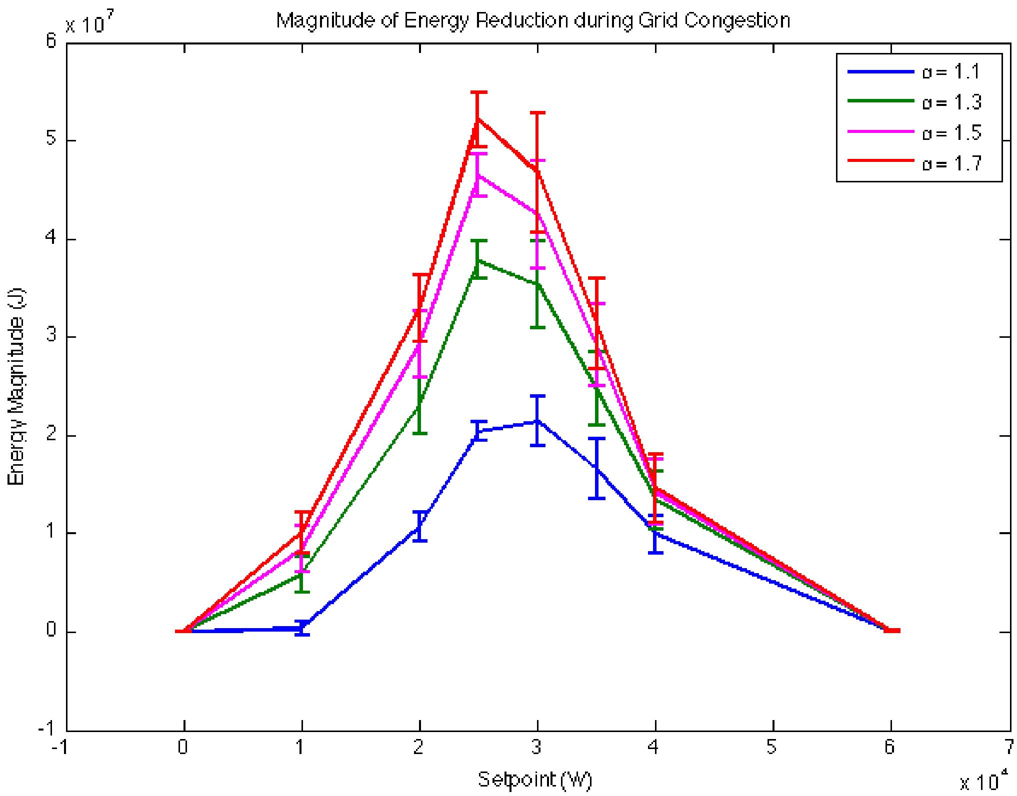

Figure 4.5: Results for the Simple USG [28]

simple USG. The performance metric defined in Equation 4.5 is computed in the y-axis of the plot.

Higher values of α translates to the allocation of higher delay budgets. It is clear from the plot that the higher α is, the higher is the gain. This is as expected. When the setpoint is set at a very high value, the gains are low. This is expected as the performance metric measures the magnitude and this will be zero if the aggregate power consumption of appliances does not go above the the setpoint. One final aspect that can be observed from this plot is that, when the value of S is low, the gains are the lowest. For all values of α, the highest gain occurs at $30k$W. This value corresponds to the average aggregate power consumption of all appliances. This behavior is not desirable. The USG must be able to produce signals that will be able to coax high gains from appliances even when the setpoint is set to be a very low value.

4.4.2 Enhanced USG

In the previous section, a simple USG was proposed. It was tested against the ASC proposed in Chapter 3. Some insights gained from this evaluation will be used to propose a more enhanced USG. The main goal of the USG is to generate signals that will maximize the performance even when the setpoint is set at a low value. One important observation from the above study is that the highest gains are obtained when the USG generates signals around the average of the aggregate power consumption of all appliances in that region.

The enhanced USG is a slightly modified version of the simple version proposed above and can be found in Equations 4.6, 4.7 and 4.8. Equation 4.6 computes the moving average ($ema(t_n)$) of the aggregate power demand ($P_a(t_n)$) of all appliances in the region. β is a value between [0,1]. Higher the value of β, the more sensitive is the moving average to the latest aggregate power consumed. High values may cause instability in the system. For this reason, β is proposed to be $\frac{1}{1800}$ which represents the moving average of aggregate power consumption over an hour.

$$ema(t_n) = (1 - \beta) * ema(t_{n-1}) + \beta * P_a(t_n) \tag{4.6}$$

According to Equation 4.7, the USG can transmit the original congestion signal $S'_c(t_n)$ if the moving average is lesser than S. In this case, the congestion signal will be in 'good' state as the aggregate power consumed by appliances is less than the setpoint.

If $ema(t_n) < S$, then

$$S'_c(t_n) = \frac{P_a(t_n)}{S} \tag{4.7}$$

In the other case where the moving average is greater than the setpoint, USG will transmit congestion signals computed according to Equation 4.8. The congestion state of the grid will now be not as high as that if Equation 4.7 is used to compute the congestion signal. This will prevent the appliances from depleting their delay budgets too rapidly.

If $ema(t_n) >= S$, then

$$S'_c(t_n) = \frac{P_a(t_n)}{ema(t_n)} \tag{4.8}$$

Figure 4.6 illustrates the results for 100 homes in Quebec when the enhanced USG is used to compute congestion signals. A comparison is made between the results from the simple USG and enhanced USG when $\alpha = 1.1$. It is clear that with the enhanced USG, the desired results have been attained. The performance gains especially when the setpoint is set to very low values are very high. This is as expected. Hence, the enhanced USG has delivered the expected performance gains.

To put the gains into perspective, a simple computation for a realistic scenario will be shown next. Suppose in Quebec, the utilities would like to minimize the use of carbon generation sources. Suppose the carbon generation sources are activated when the aggregate load in a region of 100 homes reaches 10k W. Figure 4.6 shows that the total magnitude of energy consumption can be reduced by 35 MJ in a day with the use of the proposed ASC and enhanced USG. The operation duration of all appliances are extended by 10%. For an appliance that requires 50 minutes to operate, this translates to only 5 minutes of operation extension which maybe barely noticeable by consumers. As of 2006, Quebec had 3.2 million households [25]. In this case, the average reduction of energy consumption can surmount to 12.96 MWh. This value is obtained by first computing the average gains in energy reduction per hour ($\frac{35*10^6}{24*3600}$) for 100 households. Then multiplying this value by the sets of 100 households in Quebec ($\frac{3.2*10^6}{100}$).

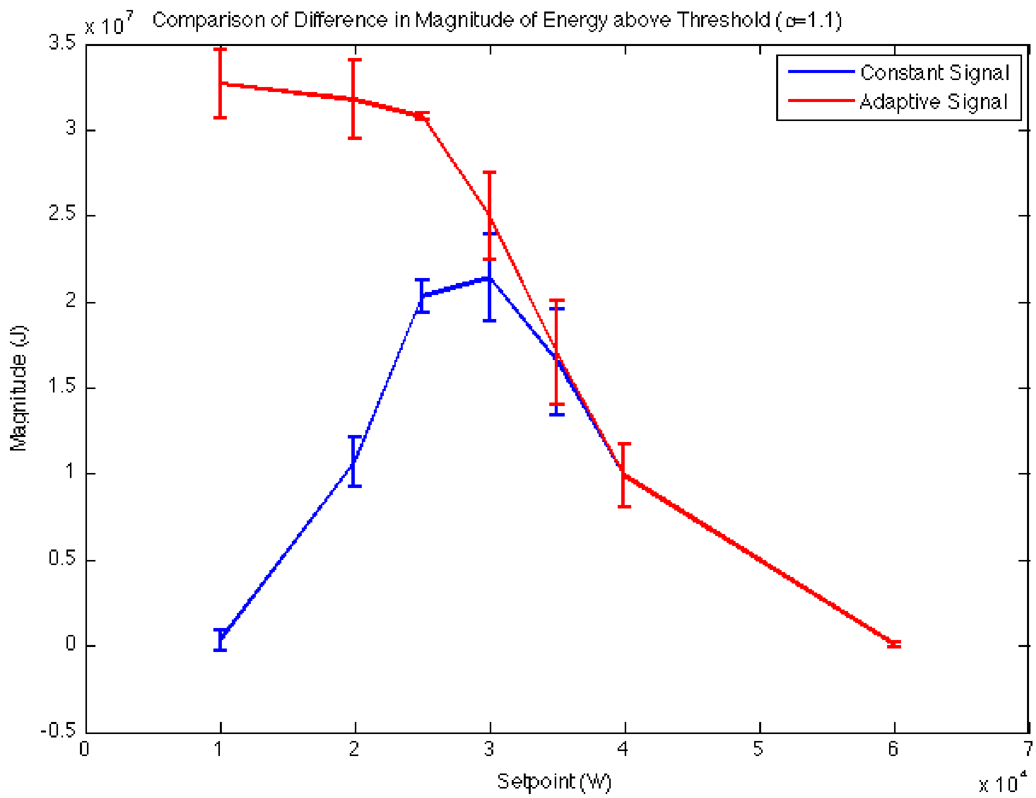

Figure 4.6: Results for enhanced USG [28]

Chapter 5

Conclusions

In this thesis, a demand response scheme for the residential sector has been proposed. This scheme is based on a property of appliances called elasticity. First the potential of this property in contributing to the reduction of aggregate peak demands was investigated. Results from this study showed that elasticity in appliances have a significant potential in reducing peak aggregate demands. Based on these results, a distributed DR scheme was proposed. This scheme consists of appliance side controllers and utility side signal generators. The proposed appliance side controller is independent of the utility's definition of congestion and functions in a distributed manner. It attempts to reduce the controlled appliances' contribution to congestion in the grid while preserving the delay budget allocated to the appliances. In order to illustrate the effectiveness of the appliance side controller, two designs for the utility side signal generator is proposed. The first one is a simple design that shows the adverse impact of inappropriate signal generation on the behavior of the appliance side controller. The second utility side signal generator design is based on the lessons learned from the simpler design. Simulations indicate that high gains can be obtained in realistic situations from the proposed demand response scheme.

Based on the results from this thesis, it can be concluded that elasticity in appliances can be used to solve various issues in the power grid such as reducing carbon footprint of generation sources, reducing infrastructure costs and etc. The designs proposed in this thesis are an illustration of the potential appliance elasticity. Hence, based on these findings, appliance manufacturers and utilities should work together to standardize a set of protocols. Governments should introduce new energy policies and facilitate further research in this area.

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