# IMPACT OF CONTROL FREQUENCY ON TRANSFORMER LEVEL DEMAND MANAGEMENT AND CONSUMER COMFORT

A Thesis by

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The following faculty members have examined the final copy of this thesis for form and content, and recommend that it be accepted in partial fulfillment of the requirement for the degree of Master of Science with a major in Electrical Engineering.

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Mahmoud Edwin Sawan, Committee Member

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Ehsan Salari, Committee Member

# DEDICATION

To my parents, my brother and my sisters

# ACKNOWLEDGMENTS

I would like to thank my advisor Dr. Visvakumar Aravinthan for all his guidance and support. I would also like to thank Abbas Gholizadeh and Suvagata Chakraborty for their thought provoking inputs. Lastly, I would like to thank all who have ever given even a single input that in anyway helped in completing this work.

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# LIST OF ABBREVIATIONS

AMI ..... *advanced metering infrastructure*

AMR ..... *automated meter reading*

ASHRAE ..... *American Society of Heating, Refrigerating, and Air-Conditioning Engineers*

CFLs ..... *compact fluorescent lights*

CL ..... *controllable loads*

CYC ..... *cyclic*

DSM ..... *Demand Side Management*

ETP ..... *equivalent thermal parameter*

HVAC ..... *Heating, Ventilating, and Air Conditioning*

LCD ..... *Liquid crystal display*

NCL ..... *non-controllable loads*

NCYC ..... *non-cyclic*

NTCL ..... *non-thermostatically controllable loads*

PAR ..... *Peak to Average Ratio*

TCL ..... *thermostatically controllable loads*

TCLs ..... *thermostatically controlled loads*

# ABSTRACT

A demand side management (DSM) scheme is proposed in this work to schedule Heating, Ventilating, and Air Conditioning (HVAC) loads, using forward dynamic programming in order to maintain consumer's thermal comfort while avoiding demand peaks at the distribution transformer. The motivation is to analyze the impact of different control signal frequencies i.e. per 15, 30, 45 and 60 minute control, from both the utility and consumer perspective. The analysis parameters are percentage reduction in peak demand, energy violation, number of violations, sustained duration of violation from utility perspective, and total deviation duration and sustained deviation duration from the preferred thermostat settings from consumer's perspective. The comparison of results is based upon permissible limits of temperature drift for each frequency as mentioned in ASHRAE 55 standards for thermal comfort. Since dynamic programming approach is used, the impact of number of states to be saved per stage is also analyzed.

In an attempt to imitate a real system and test the algorithm, a simple intuition based household load profile model is first developed. The equivalent thermal parameter (ETP) model is used to for the HVAC system with its parameters tuned to reflect ideal conditions. The algorithm then utilizes day-ahead forecast of price and outdoor temperature data to solve the scheduling problem. The constraint signal for the distribution transformer serving a group of households is generated using transformer rating and price signal from the utility. The day-ahead forecast of price signal used is downloaded from ComEd, Illinois and both the price and weather data used are for the duration 123 days from May 1$^{st}$ to August 31$^{st}$, 2012.

# CHAPTER 1

# INTRODUCTION

Demand side management among other smart grid initiatives, has gained increased attention in an attempt to defer the investment in upgrading the power grid in terms of more generating units and transmission lines. Basically, DSM includes everything that is done on the demand side of an energy system, ranging from exchanging old incandescent light bulbs to compact fluorescent lights (CFLs) up to installing a sophisticated dynamic load management system [1]. While DSM was "utility driven" in the past, it has the potential to move towards a "customer driven" activity in the near future [1]. In recent years, a number of U.S. states have adopted or are considering smart grid related laws, regulations, and voluntary or mandatory requirements [2]; at the same time the number of smart grid pilot projects has been increasing rapidly [2]. The technologies utilized in those projects are: advanced metering infrastructure (AMI), automated meter reading (AMR), distributed generation, energy storage, smart appliances and dynamic pricing. A well-developed Demand Side Management (DSM) program is expected to have impact on several applications such as peak reduction, power factor improvement, equipment life, and consumer cost reduction.

Two key demand response resources that are popular among the researchers for grid services at the residential level are namely thermostatically controlled loads (TCLs) and electrochemical batteries used in plug-in electric vehicles. This is due to the fact that both of them are capable of storing energy in some form and release when it is needed with minimum interaction with the consumers and their comfort level. The motivation behind scheduling either of them is that they are not only good at reducing peak demand, but also are good candidates for load shifting or valley filling. Among other benefits, HVAC systems are able to store energy i.e.

cooling in off peak hours and coasting during peak hours. Moreover, the user comfort level violations can be reduced by raising or dropping the thermostat to levels that does not cause much thermal discomfort as long as it's within the limits defined by ASHRAE 55 [3] standard for thermal comfort. On the other hand, other controllable appliances may impose some time delay in operation, thus create more discomfort. For example, a clothes dryer cannot be used before clothes washer, so the consumer will have to wait to operate the dryer once the washer cycle is complete. Also, the availability of programmable thermostats may help avoiding the investments in developing advanced equipment as is the case with other appliances that may require special circuits to be able to communicate with the network and control those complicated appliances like dish washer, washer-dryer etc.

In this work, the main focus is to minimize the thermal discomfort by keeping indoor temperature in close proximity to the user preferred temperature settings while attempting to reduce the peak demand at the secondary distribution transformer. The ON/OFF time constraint for air conditioners which prohibits the frequent energizing or de energizing of the compressor can be easily avoided by modifying the thermostat settings instead of directly turning on or off the controlled appliance. Therefore we chose to control the thermostat settings.

Even though significant number of work has been done to develop demand management schemes, this work differs from the literature, as it compares the impact of control interval (demand interval) on the actual benefits to the distribution grid. The control parameters are based on different control sampling rate selection and represent the impact on both the user and the utility. The motivation is to develop a framework to analyze the tradeoffs when choosing different sampling rates; based on the ASHRAE 55 standard for thermal comfort.

### 1.1 Contribution:

Forward dynamic programming algorithm is utilized in order to analyze the impact of control signal frequency that is 15, 30 and 60 minutes, on user comfort level and the transformer serving those users. The main idea is to analyze the importance of the need of using higher frequency control signals from user and transformer perspective. Any gain in the understanding of the impact of control frequency on the system will support in the design phase of smart grid implementation.

### 1.2 Out of Scope:

The current work is limited to controlling air conditioning units and only for a small number of houses. Other thermostatically controllable appliances are not taken in to account for this work as the idea is to demonstrate the impact of control frequency in general and not on the actual system.

### 1.3 Organization:

The rest of the work is organized as follows, Chapter 2 is the Literature Review, Chapter 3 is Household Load Modelling, Chapter 4 is Algorithm and Simulation, Chapter 5 is Results and Chapter 6 is Conclusion.

# CHAPTER 2

# LITERATURE REVIEW

Smart grid captured researchers' interest due to the advancement prospects that promise more efficiency and reliability for power generation, transmission and consumption. A grid is called smart when it is able to communicate with its components and thus make quicker and much efficient decisions, with or without human interaction. Unlike traditional grid, which relies more on human interaction, the smart grid is however expected to have lesser human interaction. For instance, in case of a power outage in a traditional system, the consumer has to complain about the outage and bear the delays; meter reading and billing requires more man power; these tasks can be taken care of with some form of communication with the grid. A typical smart grid vision is expressed in Fig. 1 [4].

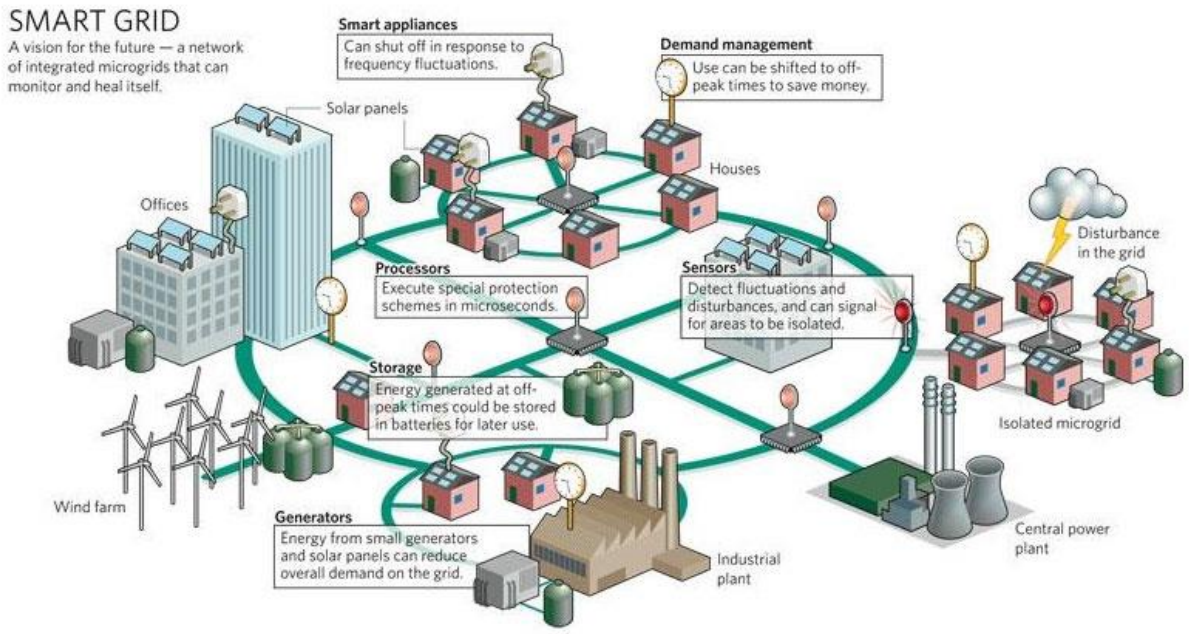


Fig. 1. A typical smart grid vision

The Smart appliances include any appliance that can communicate/respond to the control signals sent to them by the grid or sub component of the grid. The sensors and processors should work closely to respond to different types of disturbances. The storage system can be batteries, pumped storage etc. that helps in storing the energy when it's off peak hours and release during peak hours.

Traditionally the grid's flow was bottom up, i.e. the generation units used to respond to the demand. Demand response enables top to bottom approach in which the appliances/loads respond in accordance with the available resources. Smart household appliances can play a key role in this scenario by responding to the control signals sent by the utility in order to control the load.

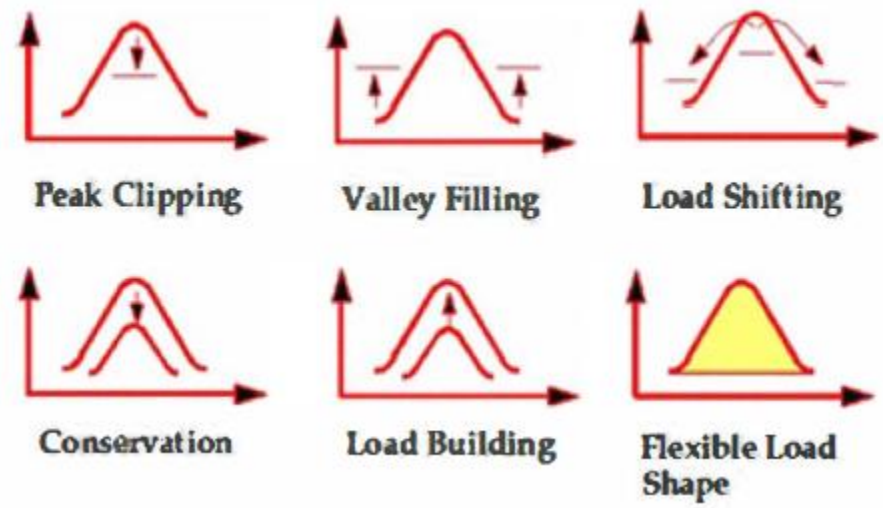


Fig. 2. Demand side management categories

Fig. 2 [5] represents the six categories of demand side management (DSM) that are expected to be achieved by demand response techniques. Peak clipping refers to direct load control to make reduction of the pick loads, while valley filling focuses on constructing the off-peak demand by applying direct load control. These two approaches focus on reducing the

difference between the peak load level and the valley load level in order to mitigate the burden of peak demand and increase the security of the distribution network. Load shifting combines the previous classic load management forms and shifts loads from peak time to off-peak time. This approach is widely applied as a most effective load management strategy in current distribution networks and it takes advantage of time independence (or flexibility) of loads. Storage heating or cooling systems based on the concept of shifting electricity usage period can be implemented to ameliorate the high peak demand condition by through energy storage in the form of heat/cold [6].

The broader scope that the smart grids encompass attracts so many industries in this arena. Fig. 3 [7] represents the involvement of leading players by market segment.

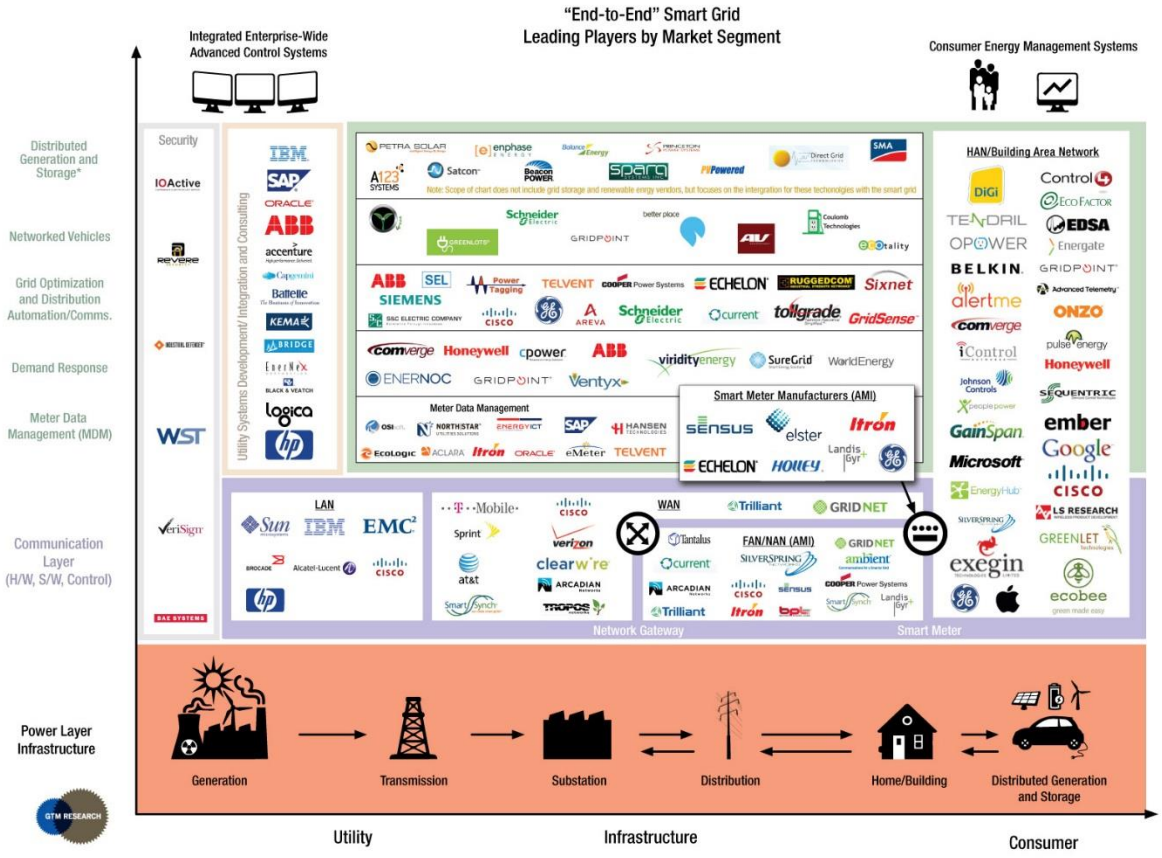


Fig. 3. Involvement of leading players by market segment

Although the term smart grid is more generic, smart grid is differently seen in different geographical areas. For instance, where USA is more interested in peak reduction and CO2 emission reduction, Asian countries leaned more towards gaining reduction in non-technical losses (NTL) like energy theft. Fig. 4 [8] shows some of the countries and their interests in smart grid.

| Country | Government Policies/ Mandates | Environmental Goals | Electric Vehicle Integration | Renewable Integration | Reliability Concerns | Financial Incentives | Energy Efficiency Goals | Increasing Demand | Economic Competitiveness | Geographic Grid Constraints | Energy Security Goals | Energy Theft Reduction |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Australia | ● | ● | | ● | ● | ● | ● | | | | | |
| Canada | | ● | | | | | ● | ● | | ● | ● | ● |
| China | | ● | | ● | | ● | ● | ● | ● | ● | | |
| Denmark | ● | ● | ● | ● | | | | | | | | |
| Germany | ● | ● | | ● | | ● | | ● | | | ● | |
| India | | | | | ● | | ● | ● | ● | ● | | ● |
| Japan | | ● | ● | ● | | ● | | | | | | |
| South Korea | | ● | | ● | | ● | ● | | | | | |
| Spain | ● | | ● | ● | | ● | | ● | | | | |
| United Kingdom | ● | ● | | | | ● | | | ● | | ● | |

Fig. 4. Countries and their smart grid interests

Appliance's usage profiling can be very helpful for the smart grids and can support DSM programs since it enables the system to understand the user activities and thus better forecast the load profiles. Appliance identification strategies were developed in [9] - [12]. In [9], a V-I trajectory based taxonomy was presented. The appliances, based on their trajectories are then divided into groups representing similar appliances. In [10], a load monitoring system is presented based on S-Transform. However, the methodologies require load monitoring at appliance level and not the aggregation point, i.e. the main meter. This problem was targeted in [11] and [12] where the appliances are identified at the aggregation point and thus the need of individual monitoring was suppressed. Usage profiling will also help in developing load specific

models and better forecast each appliance's demand and will ultimately supplement the development of controlling algorithms.

In terms of controllability, household load can be classified as controllable loads (CL) and non-controllable loads (NCL). CLs can be further categorized as thermostatically controllable loads (TCL) and non-thermostatically controllable loads (NTCL). Examples of TCLs are HVAC systems, refrigerator, freezer etc. Appliances that can be switched on/off directly or can be programmed for their operation fall in the other category.

Work done in [13] and [14] is primarily focused on the controlling of Non-thermostatically Controllable Loads (NTCLs) responding to DSM signal. However a direct control method as proposed in [13] and [14] is not feasible for Thermostatically Controllable Loads (TCLs) due to the constraints like acceptable thermal range and minimum compressor on/off time. Controlling appliances locally, i.e. for each individual household separately brings another concern that there remains no coordination at the community level. Moreover, expanding them to multiple households require information about the usage patterns of other appliances. In [15] an energy consumption scheduling model is presented in the presence of local micro generation which can be expanded from household to the community level. The test cases used for simulations are with arbitrary load profiles of some appliances, unable to control TCLs, and does not represent an actual system. The goal, similar to most of the work available, is to save energy usage cost to the consumer. Furthermore, the algorithm is unable to handle large number of appliances and demands high computational power. Similarly, in [16] a power consumption scheduling scheme, using arbitrary load profiles of NTCLs, handles multiple tasks to schedule. The analysis of algorithm is based upon the impact of number of tasks on the execution time for a constrained environment, which actually did far better than a non-constrained environment.

Significant work is done to manage the demand of multiple customers. For example, in [17] - [20] game theory is utilized to schedule loads at a community level with minimum information exchange. The algorithm proposed in [17] was able to reduce Peak to Average Ratio (PAR) and the total cost in the system. Basically, the game among the consumers is to schedule appliances so that the overall cost of supplying the energy demand is reduced, and ultimately reduce the cost to each consumer. Real time pricing is utilized in [18] to optimally schedule household loads in an attempt to reduce cost and waiting time to the consumer. The automated system is proposed so that the consumer does not have to respond manually to continuously changing prices as it requires training and understanding of the system as well as constant and careful input from the consumer. The work was extended in [19] to realize PAR reduction when compared to percentage of schedulable loads available. The work was further extended in [20] to utilize battery storage system for balancing the supply and demand by charging the batteries at low demand periods and discharging when the demand is high. Finally, the effect of battery capacity and number of users equipped with battery storage system was analyzed. However, throughout the work related to game theory was mostly based on reduction in cost and PAR, and not the user discomfort.

In [21] - [27], TCLs are the main focus. A real time scheduling of deferrable load such as electric vehicles and TCLs is presented in [21] and performance of three scheduling algorithms is compared. The analysis was done from the grid point of view i.e. the impact of scheduling appliances on the reserve capacity. In [22], an algorithm to schedule water heater based on different cost and comfort settings is presented; utilizing the forecasted temperature and price data. However, the model is local to the each house and the idea of immediately turning off an appliance when the cost is high is not implementable to HVAC units as HVACs pose constraints

such as *minimum off time for compressor* (which is usually 5 minutes) hence cannot be switch ON/OFF frequently. The HVAC units have some operating constraints that restrict the way they need to be controlled. For instance, when the compressor of an HVAC system is turned "off", the air pressure in the chamber is high and a certain amount of time is needed for the pressure to even out. Restarting the compressor under pressure may cause physical damage [27]. The aggregated models and control strategy proposed in [28] explicitly takes into account the lockout effect of HVAC units which prohibits the unit from turning back "ON" before a certain time. Also this constraint is incorporated in the work done in [23], which demonstrates a comparison of varying the temperature upper and lower bounds. Temperature readings from an office building were used to model this system in order to maintain thermal comfort and power consumption, where multiple units are working in coordination to maintain temperature in a facility. This is very helpful when there is a system available to identify appliances, learn the usage pattern and tune the respective models to help the scheduling algorithms schedule. Then a comparison of different algorithms is compared for the performance metrics such as time to reach comfort band, number of switching i.e. ON/OFF and discomfort duration. Although comparing different comfort bands for the user, it is not giving the control to the user, thus forcing the consumer to stay at higher temperatures for a while.

The aggregated models and control strategy proposed in [24] also explicitly takes into account the lockout effect of HVAC units which prohibits the unit from turning back "ON" before a certain time. Notice that this is a concern when the control signal frequency is very high, hence an algorithm with low frequency for control signal can also help avoid this concern. The implementation of such a system is however, does not seem practical as first, it requires high computational power at the aggregation point to schedule 5000 HVAC units and secondly, the

benefits cannot be seen at the distribution transformer as the main idea is to reduce peak on system wide level. Then in case a lockout of majority of the HVAC's population, the algorithm will not be able to perform well. Lastly, the communication requirements for the data and control signals will increase in order to serve a large number of HVAC units at once. A day-ahead scheduler is presented in [25] promising savings in consumer cost, but the user is not given flexibility of choosing temperature set points and deviation from the set point. In [26], a low computational cost scheme using look-ahead control approach is proposed, however the controller requires more than one day data.

In majority of the work mentioned above, the main goal remained the reduction in cost. Work related to user comfort, has either a high computation resource consuming algorithms or has not given any control to the consumer. Moreover, none has actually discussed the interdisciplinary goals such as the tradeoffs among the power system and the communication system. Improving power system may need some compromising in communication system and vice versa. This work deals in analyzing the trade that can be seen while trying to improve either of the systems so that they can work together in the most efficient manner and the system designers can have improved view before making decisions. To this, a comparison of control signal frequencies is presented. A higher control frequency could be better for the power system as it gives more information of the system and thus better control but at the same time is a burden from the communication and computation point of view.

# CHAPTER 3

# HOUSEHOLD LOAD MODELLING

The first step of this work is to determine the load shapes of different appliances used at the residential level. At the beginning of this work, limited appliance level data was available for modeling purpose. Therefore this work recorded at developed load models for different residential level appliances. The available residential level load curves that are available in the literature were used to validate the aggregated individual house load shape. The following subsections details the modeling of individual residential loads.

## 3.1 Data Recording:

Power profile of few appliances was recorded using Eagle 120 power monitor to analyze their operating behavior which helped in generating the base load profile for different houses. Fig. 5(a) represents electric load profile for a household refrigerator. It was noticed that the changes in compressor on-time for a refrigerator is due to the following three reasons,

1. Door opening
2. High room temperature
3. High cooling load

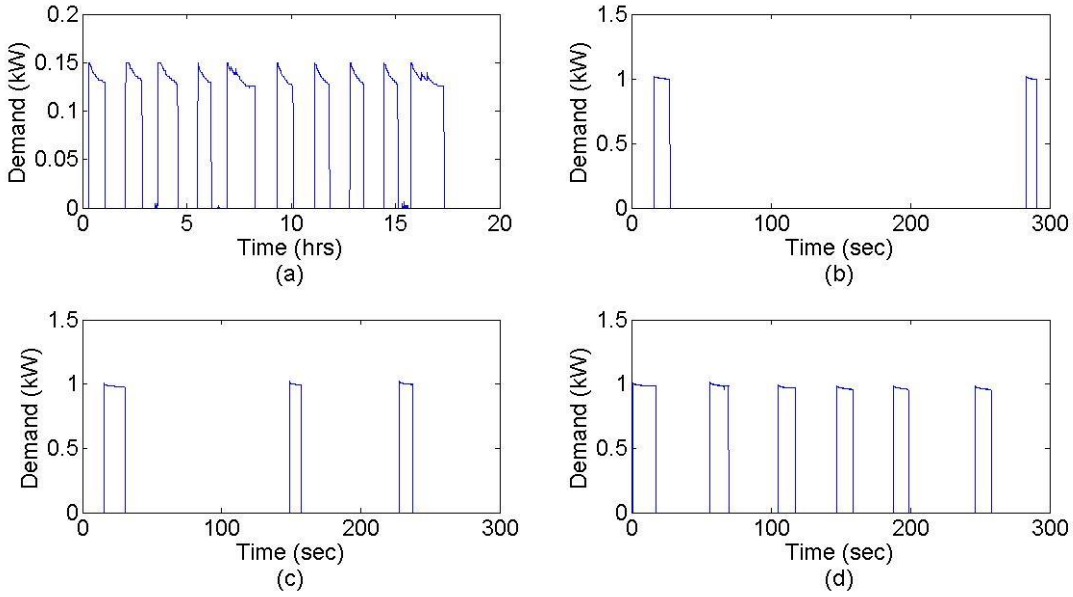


Fig. 5. Recorded individual load data (a) Refrigerator, (b) Electric iron with minimum setting, (c) Electric iron with medium setting, (d) Electric iron with maximum setting

It should be noted in the Fig. 5(a) the small spikes recorded between actual ON cycles are due to the door opening event which causes the internal bulb to turn on and changes the ON time of the immediately following cycle. The compressor usually remains on for 40 to 80 minutes depending upon the usage. Different selector settings were not analyzed for refrigerator as the same ETP model as that of air conditioning is used to model this load, as explained later.

Fig. 5(b) represents an electric iron's load profile with the selector knob set to minimum. Notice that the cycles are very less frequent and consequently the average load contribution for this case is insignificant. The selector knob was then set to midpoint as shown in Fig. 5(c). Again, the on cycles are very less frequent i.e. only 3 cycles of maximum 20 seconds duration, within the 4 minutes of recording. Finally, Fig. 5(d) represents the load profile with selector set to maximum setting. Notice the difference in frequency of ON cycles which will have significant impact on the average demand posed by this appliance. It was noticed that the average ON

duration in a minute remains 10 to 20 seconds. Lower selector settings also keep the iron on for approximately the same duration, as it has to just maintain the iron plate's temperature, however, the cycles become less frequent. The electric iron remains on for 25% to 40% of the time during the operation, and consequently consumes from 25% to 60% of the max rating per minute when the selector is set to max. The different ON-times during the operation are due to pick up from cold iron, pressing/ironing and on stand events.

The rest of the electrical appliances selected for this work i.e. microwave oven, fans, lights and laptops are all non-cyclic loads and remain at their rated power level when ON and zero when OFF. Some sample recordings are as follows.

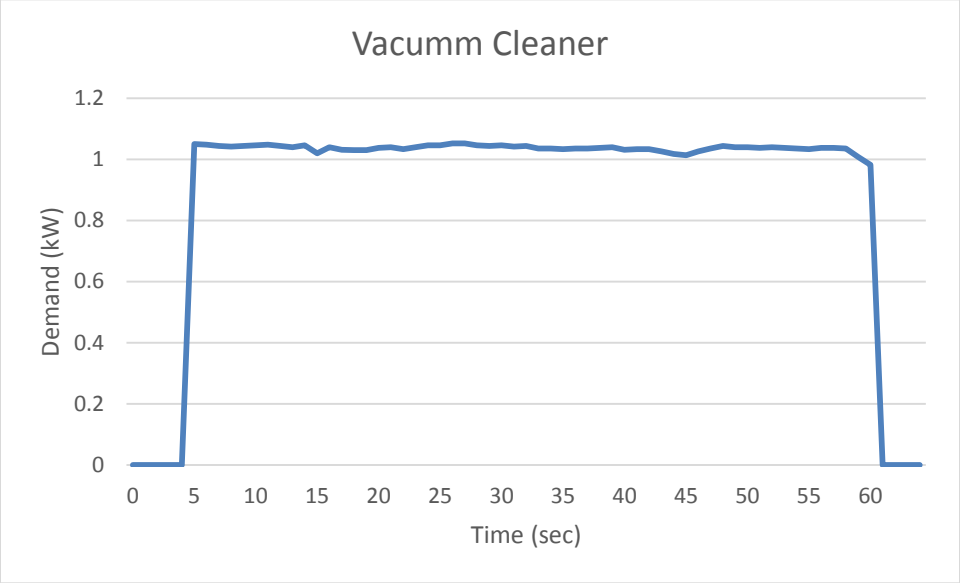


Fig. 6. Vacuum cleaner ran for 55 seconds

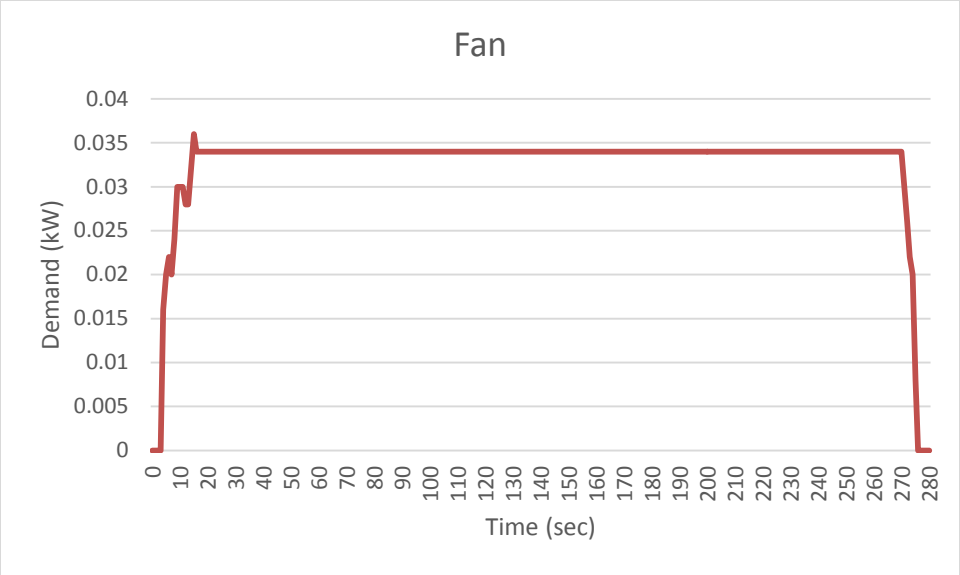


Fig. 7. A fan load profile for approximately 5 minutes

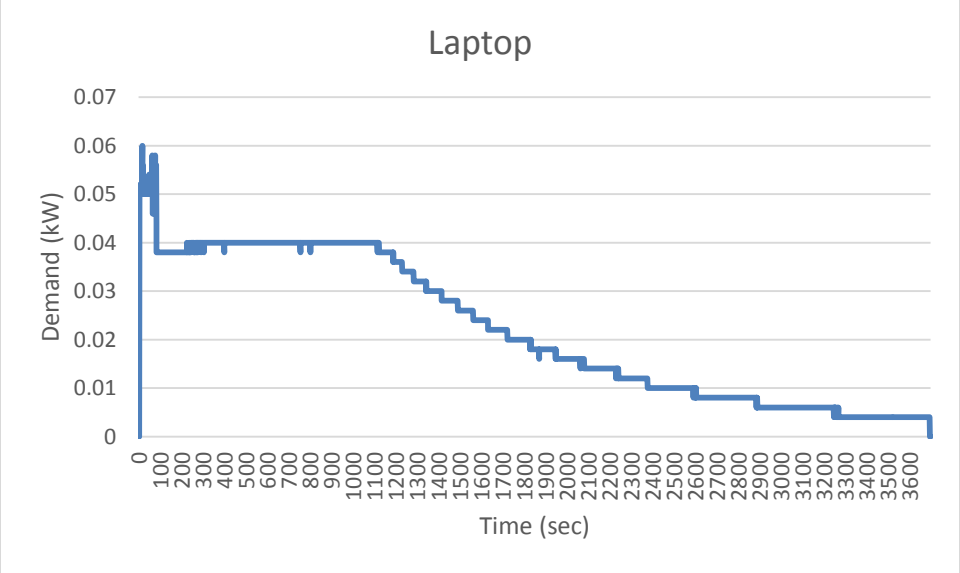


Fig. 8. A laptop charged for 1 hour

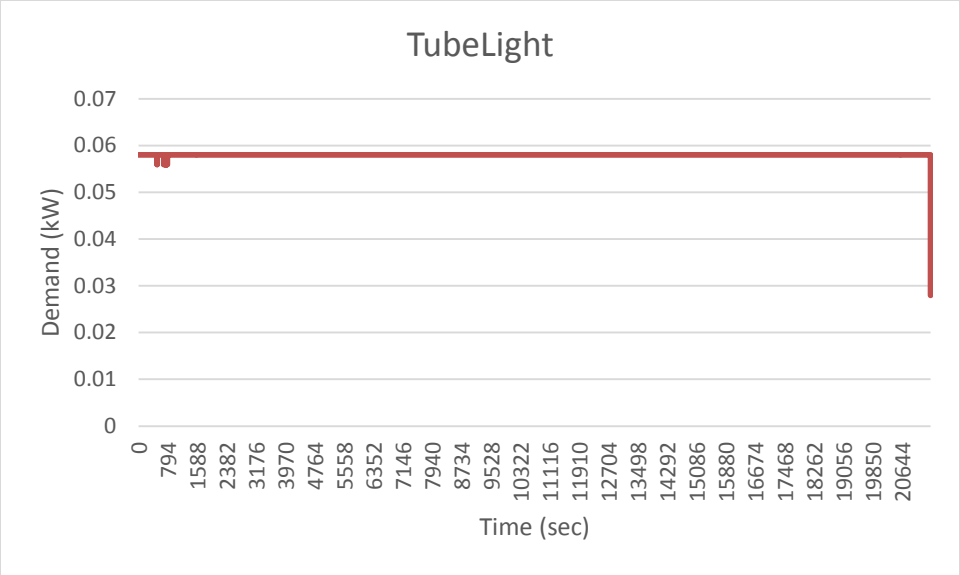


Fig. 9. Tube lights on for 6 hours

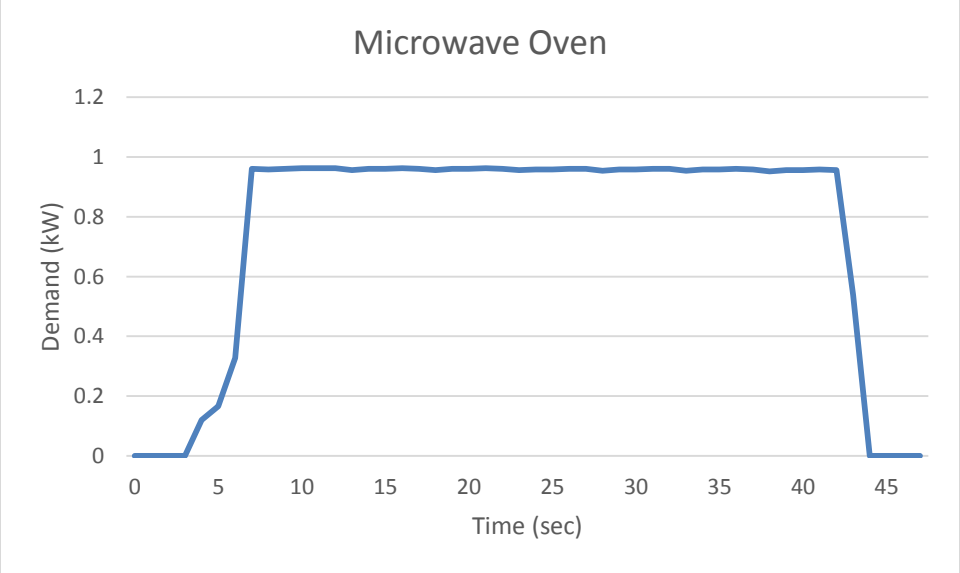


Fig. 10. Microwave oven load profile operating for 45 seconds

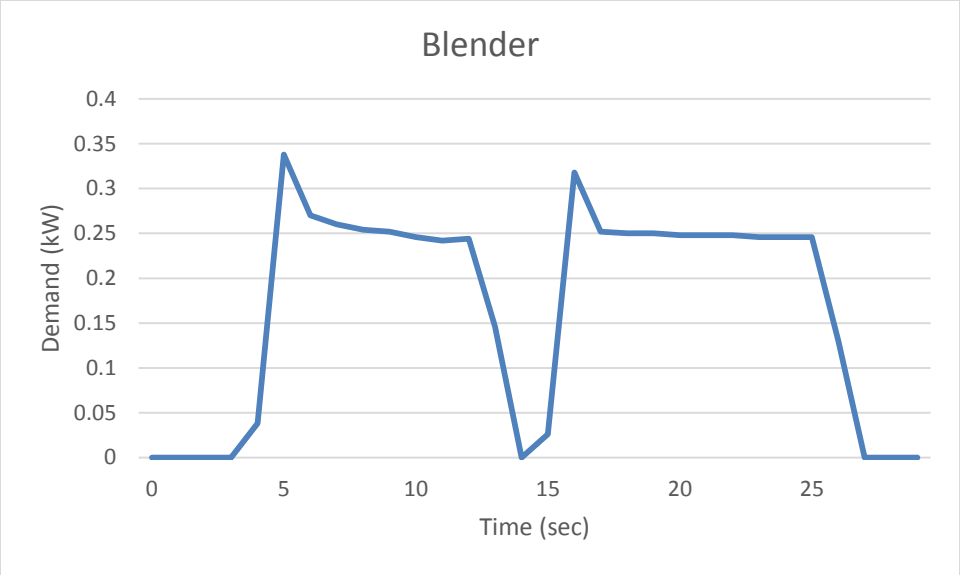


Fig. 11. A blender, turned on/off during operation

Note: Blender and vacuum cleaner are not used in household load profile generation.

### 3.2 Base Load:

A base load profile was needed for each house in order to imitate a real system. All load types except air conditioning and, which remains there most part of the day are defined as base load. Some of the appliances such as electric iron, laptops and microwave oven are included due to their high power demand or usage frequency. Since household load modelling is not the main focus of this work, a simple, intuition based scheme was developed. More sophisticated techniques including probabilistic methods and Markov chain based models can be found in [28], [29] and [30].

### 3.3 Load Classification:

Household appliances can be classified as cyclic (CYC) and non-cyclic (NCYC) based on their demand profile pattern. Cyclic loads change states during their operation e.g. HVAC,

refrigerator, and freezer, electric iron etc., whereas non-cyclic loads remain at a certain power level while operating e.g. space lighting, fans, laptops, microwave ovens, LCDs etc.

### 3.3.1 Cyclic Loads

#### 3.3.1.1 Air Conditioner

The modeling approach that is used to estimate thermal loads is called an equivalent thermal parameter (ETP) modeling approach. This modeling approach has been chosen for the current work because it has been proven to reasonably model residential (and small commercial building) loads and energy consumption and also because it is based on first principles [30].

$$\dot{T}_{air} = \left\{ \frac{1}{R1 \cdot C_{air}} - \frac{1}{R2 \cdot C_{air}} \right\} \cdot T_{air} + \frac{T_{mass}}{R2 \cdot C_{air}} + \frac{T_{out}}{R1 \cdot C_{air}} + \frac{Q}{C_{air}} \tag{1}$$

$$\dot{T}_{mass} = \frac{T_{air}}{R2 \cdot C_{mass}} - \frac{T_{mass}}{R2 \cdot C_{mass}} \tag{2}$$

where, $C_{air}$ is air heat capacity (Btu/$^0$F), $C_{mass}$ is mass (of the building and its content) heat capacity (Btu/$^0$F), $T_{out}$ is ambient temperature ($^0$F), $T_{air}$ is air temperature inside the house ($^0$F), $T_{mass}$ is mass temperature inside the house ($^0$F), $Q_h$ is heat rate for HVAC (Btu/hr.), $Q_i$ is heat rate from other appliance, lights, people etc. in the residence (Btu/hr.), $Q_s$ = heat gain from solar (Btu/hr. or watts), $R1 = 1/UA_{insulation}$, $UA_{insulation}$ is heat gain/loss coefficient (Btu/$^0$F.hr) to the ambient, $R2 = 1/UA_{mass}$, $UA_{mass}$ is heat gain/loss coefficient (Btu/$^0$F.hr) between air and mass, $Q = Q_i+Q_s+u*Q_h$ and $u$ is on/off control variable.

Therefore the Euler's equivalent of the model is,

$$T_{air}(k+1) = T_{air}(k) + h \cdot \left\{ \frac{1}{R1 \cdot C_{air}} - \frac{1}{R2 \cdot C_{air}} \right\} \cdot T_{air}(k) + h \cdot \left\{ \frac{T_{mass}(k)}{R2 \cdot C_{air}} + \frac{T_{out}(k)}{R1 \cdot C_{air}} + \frac{Q}{C_{air}} \right\} \quad (3)$$

$$T_{mass}(k+1) = T_{mass}(k) + h \cdot \left\{ \frac{T_{air}(k)}{R2 \cdot C_{mass}} - \frac{T_{mass}(k)}{R2 \cdot C_{mass}} \right\} \quad (4)$$

where, $h$ is sample height in hours i.e. the step size, in our case is 1/60 hour or 1 minute.

The relay in TCLs needs to be molded when a controller is developed. The output frequently changes according to minute temperature changes (temperature does not remain constantly at a particular level due to various changes in the environment and can force the relay to respond to those changes), and shortens the life of the output relay or unfavorably affects some devices connected to the temperature controller. To prevent this from happening, a temperature band called hysteresis is created between the ON and OFF operations [31]. See Fig. 12.

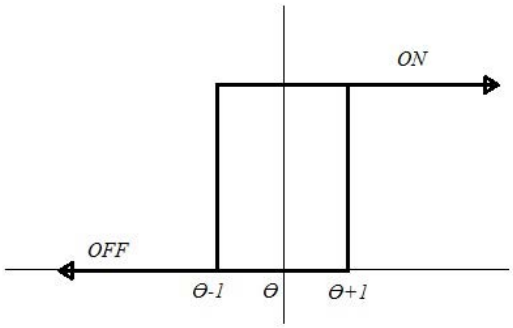


Fig. 12. Hysteresis loop for the thermostat relay

The demand profile can be generated thus,

$$P_{ac}^{n}(k) = u_{ac}(k) \cdot P_{ac_rated}^{n} \quad (5)$$

The thermal parameters for each house can be different and demand a survey or knowledge of typical ranges for them to be used. This is where appliance identification techniques could help

in a real system by learning about appliance specific demand and behavior and then utilize the information to tune the respective model's parameters. Therefore, in an attempt to avoid the mentioned demands, i.e. doing surveys or having an appliance level identification system, we chose to tune the ETP model parameters to represent the most favorable conditions. Based on the ASHRARE 55 [32], table I show limits on temperature drifts. Using this information, we tweaked the parameters to match the requirements for each house with 98 $^0$F as the design day outdoor temperature for Wichita, KS and 74 $^0$F as the desired set point [33]. Fig. 13 shows a sample internal temperature variation with respect to the outdoor temperature.

**Table I: Limits on Temperature drifts**

| **Time Period (hrs.)** | 0.25 | 0.5 | 1 | 2 | 4 |
|---|---|---|---|---|---|
| **Max Operating temperature change allowed (Degree F)** | 2 | 3 | 4 | 5 | 6 |

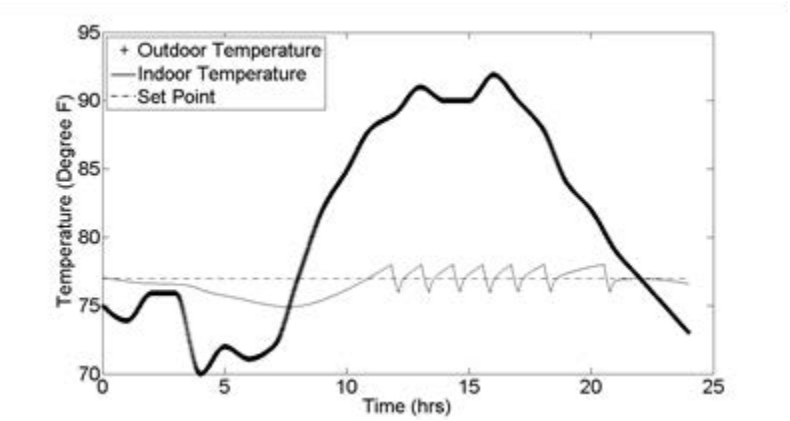


Fig. 13. Indoor temperature profile against outdoor temperature for thermostat set to 77 $^0$F

### 3.3.1.2 Refrigerator

The same model as that of air-conditioning is used for refrigerator, but with different thermostat settings and thermal parameters. Power profile of few refrigerators was recorded using Eagle 120 [34] power monitor to analyze their operating behavior. The door opening event

plays a critical role in defining the load profile for refrigerators. Based on this observation, in order to imitate random door opening events, the outdoor temperature (i.e. indoor house temperature) during those events was changed. To imitate different durations of door opening events, the range of outdoor temperature was randomly selected between 120 $^0$F – 130 $^0$F. For normal operations, the outdoor temperature is randomly selected between to 74 $^0$F – 79 $^0$F for all houses. The events are induced for morning between 5:00 a.m. to 7:00 a.m., afternoon between 12:00 p.m. to 1:30 p.m. and evening between 7:00 p.m. to 8:00 p.m. The demand profile is then generated using,

$$P^n_{refri}(k) = u_{refri}(k) \cdot P^n_{refri_rated} \tag{6}$$

The range and power level for refrigerator's thermostat setting is selected randomly for each unit between 35 to 39 $^0$F and 0.160 to 0.240 kW respectively. Fig. 14 represents a sample demand profile for household refrigerator. Notice the change in cycle width around 6:00 a.m., 12:00 p.m. and 8:00 p.m.

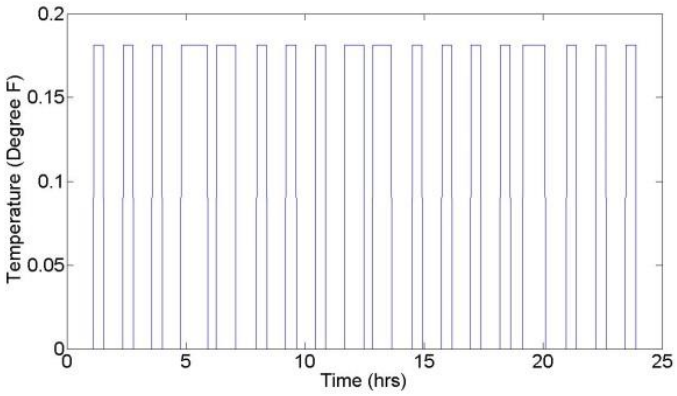


Fig. 14. Demand profile for household refrigerator

#### 3.3.1.3 Electric Iron

Electric iron is a short duration load, typically 15 to 30 minute, with high demand requirement. Although cyclic in nature, the load profile as mentioned in previously, cycles very frequently between ON and OFF state and thus does not require finer scale (per second) modelling. The cycles can start any time during each minute and thus on average can demand 25% to 60% of the rated value. It was assumed that electric iron is used more on weekends than it is used on weekdays.

First of all, total number of electric irons was chosen randomly between 1 and 2 for each house. Then the number of events for the whole day was chosen for each appliance with 1 being mean and 0.3 being the standard deviation. This means that the majority of the time, number of events for the appliance will remain between 0 and 2. Then the time of event is chosen from the set,

$wd \in \{7, 21\}$ and,

$we \in \{11, 17, 21\}$

where,

*wd* and *we* represent weekday and weekend respectively,

The standard deviation of 10 minutes is chosen for each event. And finally, the mean and standard deviation for the duration of usage were chosen as 10 minute and 2 minute respectively. Using these daily event occurrence times, per minute load profile for electric iron is generated from the range mentioned in equation (7). Notice that the electric iron's rated power is never achieved. This due to the fact that we are averaging the demand on per minute basis and our analysis on electric iron's load profiles showed that it remains below 60% of the rated power.

We chose the mean value of 42% of $P^{rated}$ with the standard deviation of 6% of the rated power to generate electric irons load profile.

$$P_{ei}(k) = \begin{cases} 0 & if\ sw = OFF \\ P_{rated} & if\ sw = ON\ \ p_k(on) \geq \tau \\ 0 & if\ sw = ON\ p_k(off) \leq \tau \end{cases} \tag{7a}$$

$$0.25 * E_{ei}^{rate} \leq P_{ei} \leq 0.6 * E^{rate}_{ei} \tag{7b}$$

where, $P_{ei}$ is electric iron's demand in kW for the interval $k$, and $P_{rated}$ is 1 kW. Normal distribution is used for each appliance with the mean and standard deviations mentioned in Table II, representing the parameters for appliances including NCLs discussed later.

**Table II: Parameters used for household appliances for load generation**

| | Electric Iron | | Laptop | | Oven | | Fan | | Lighting | |
|---|---|---|---|---|---|---|---|---|---|---|
| | wd | we | wd | we | wd | we | wd | we | wd | we |
| **Event Mean** | {7, 21} | {11, 17, 21} | {19, 22} | {13, 19, 22} | {7, 19} | {7, 13, 19} | 19 | {11, 16, 19, 22} | {6, 19-22} | {6-7, 13, 15, 18-22} |
| **Event Standard Deviation** | 10 | | 10 | | 10 | | 20 | | 20 | |
| **Mean Duration** | 10 | | 90 | | 5 | | 200 | | 5-40-120-300 | |
| **Standard Deviation of Duration** | 2 | | 10 | | 2 | | 50 | | 2-10-30-40 | |

### 3.3.2 Non Cyclic Loads:

#### 3.3.2.1 Lighting Load

Using the parameters mentioned in Table II above, with an increment of 0.005 kW, the power ratings in kW, used for lighting load when ON are in the range,

$$0.010 \leq P_{lights}^{rated} \leq 0.060 \tag{8}$$

To imitate different usage patterns, lighting load is divided into two groups. More frequent, i.e. for rest rooms etc. and less frequent, i.e. for rooms etc. That is why the mean duration and standard deviations mentioned in the table for lighting load have varied range. Since the load profile was generated for multiple days, the status of lighting load was carried to the next day to keep it more realistic.

#### 3.3.2.2 Fans

This load type is more consistent and can remain there for longer duration especially at night time and mid-day. Again, using the parameters mentioned earlier in Table II the load profile for fan load is generated. Similar to lighting load, the status was carried to the next day. The power rating of fan load in kW is chosen from the range,

$$P_{fan}(k) = \begin{cases} 0 & if\ p(sw) \le \tau \\ P_k & if\ p(sw) \ge \tau \end{cases} \tag{9a}$$

$$0.060 \le P_{fan}^{rated} \le 0.090 \tag{9b}$$

#### 3.3.2.3 Laptops

Laptops can take anywhere between 60 to 120 minutes to completely charge. Although, compared to the rest of the load, the demand is very low, 0.060 to 0.070 kW in most cases, we added this load as there can be multiple number of this load type in a house, charging at different times. Again, using the parameters mentioned in Table II, the load profile was generated with the power ratings in kW chosen from,

$$0.060 \le P_{laptop}^{rated} \le 0.070 \tag{10}$$

#### 3.3.2.4 Microwave Oven

Similar to electric iron it can create short duration peaks mostly during early morning, afternoon and evening. It is modelled to have duration of anywhere between 1 minutes to 9 minutes in most cases, multiple times during mornings, afternoons and evenings and its power rating is represented mathematically by,

$$0.900 \le P_{mw}^{rated} \le 1.100 \tag{11}$$

### 3.4 Load Profile Generation:

Each load $I$ and its demand $P_i(k)$ for $k^{th}$ interval is then used to first generate the per minute base load profile for each appliance. To simulate the fact that an event could occur any time within a minute, $P_i(k)$ is divided by a random number (*rnd*) for the first and last interval of operation, where $rnd \in \{1, 2, \ldots, 60\}$.

$$P_i = \begin{cases} P_i / rnd & for\ k = start \\ P_i & for\ start + 1 \le k \le end - 1 \\ P_i / rnd & for\ k = end \end{cases} \tag{12}$$

This is done for all loads other than air conditioner and refrigerator as these two are modelled differently. The aggregated load $AL$ profile for $N$ houses at any instant $k$ is thus,

$$AL(k) = \sum_{n=1}^{N} P_{refri}^{n}(k) + \sum_{n=1}^{N} \sum_{i=1}^{I} P_i^n(k) \tag{13}$$

A sample aggregated load profile of 5 houses for the duration of 4 months, excluding air conditioning load is shown in Fig. 15. Notice some part of the demand is increased in the midsection between 12:00 p.m. to 4:00 p.m. This represents weekend load and is meant to imitate that more people are at home during weekends. The low maximum demand for 5 houses is due to very small number of appliance used for each house. Inclusion of more appliances like electric stove, electric water heater, kettle, television, freezer etc. would help; however, the main interest was just to get a typical load profile.

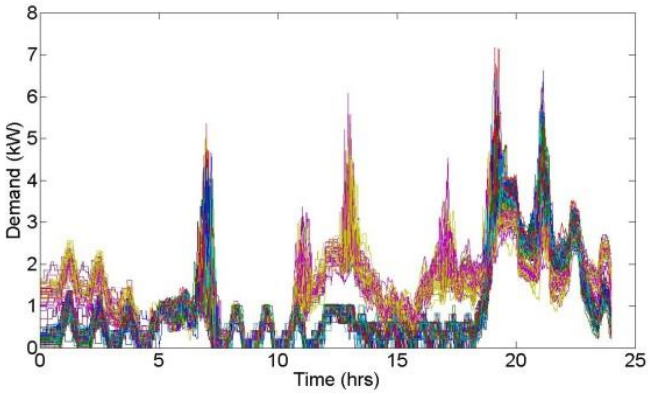


Fig. 15. Aggregated load profile of 5 houses for 123 days

# CHAPTER 4

# ALGORITHM & SIMULATION

The objective function is to minimize the variation in user's preferred thermostat setting for the air conditioning load respecting the power and thermal constraints, in other words, minimizing the user discomfort while attempting to reduce the peak demand at the aggregation point i.e. the transformer. The objective function is therefore,

$$\min \sum_{k=1}^{K} \sum_{n=1}^{N} \left\{ \theta^n(k) - \tilde{\theta}^n(k) \right\}^2 \tag{14}$$

where, $N$ is the number of air conditioning units, $\tilde{\theta}^n$ is the user's preferred thermostat setting and, $\theta^n$ is optimized temperature setting for interval $k$.

Preferred temperature range provided by the user is considered constant for the whole day. Thus the optimization problem is subject to,

$$\theta^n_{\min} \le \theta^n \le \theta^n_{\max} \tag{15}$$

And the $P_{max}$ constraint is,

$$\sum_{n=1}^{N} P_{ac}(k) \le P_{\max_ac}(k) \tag{16}$$

where, $P_{max_ac}$ is the maximum power constraint at $k^{th}$ interval provided by the utility for the aggregation point i.e. the transformer serving $N$ houses.

An algorithm using forward dynamic programming to find the optimum solution to the problem is written based on day-ahead data of temperature and price signal. The motivation behind using forward dynamic programming is that the appliance commitment problem is similar to unit commitment problem on generation side. In power plant unit commitment problem, there are a number of generating units available with their operating constraints and cost of operation

known ahead of time. To serve the expected demand, combinations of units with minimum cost, respecting all the constraints are saved for the whole day initially with multiple routes. Then in the backward direction, the total minimum cost route is selected.

In appliance commitment problem, the same can be applied to TCLs units. With day-ahead information about the constraint signals and the expected demand from each appliance, to make decisions based on the deviation from thermostat settings as the cost and available combinations for the number of units to be served, the problem can be solved.

To determine number of maximum possible states per interval for each control frequency, the information from Table I is used. Fig. 16(a), Fig. 16(b) and Fig. 16(c) demonstrate the steps that can be taken per interval for 15, 30 and 60 minute control, respectively.

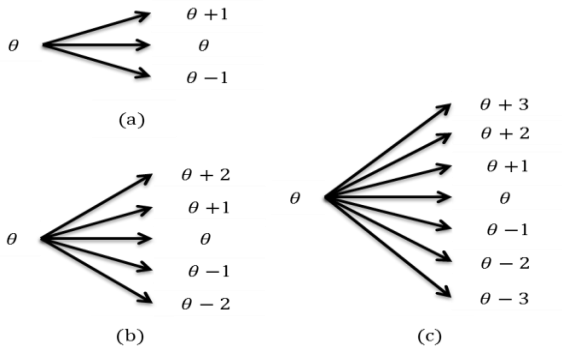


Fig. 16. Possible steps for (a) 15 minute control, (b) 30 minute control, (c) 60 minute control

For instance Fig. 16(c) shows that in one hour, there are 7 possible (steps) for the $\Theta$ to choose from i.e. it can choose to directly set the temperature 1, 2 or 3 degrees up or down. However, as can be seen in Fig. 16(a) which is representing 15 minute control, the ASHRAE standard limits the range to only 1 degree up or down. The maximum possible states per stage based on the steps can therefore be calculated as,

$$states = steps^{N} \tag{17}$$

In order to avoid new peaks that usually show up when DSM programs are utilized, the power constraint signal was generated based on the price signal. The motivation behind using the price signal to determine the constraint signal at transformer level is that, firstly, the utility is able to determine the power constraint for each transformer at distribution level. Secondly, the price signal indicates the system operating conditions incorporating both wholesale and retail markets. This can be used as an indicator to determine the load that can be connected. When the load is shifted in peak hours, the difference between the desired demand based on the price signal and the expected demand after the demand response is minimized. This will result in the actual price signal deviating less from the forecasted signal thus enabling the wholesale market to plan in advance and reduce the reserves. Moreover, managing load at the transformer level will also help in maintaining the desired load on each distribution transformer and thus will support equipment live improvement programs.

Fig. 17 represents the flow chart of the algorithm developed to solve the problem.

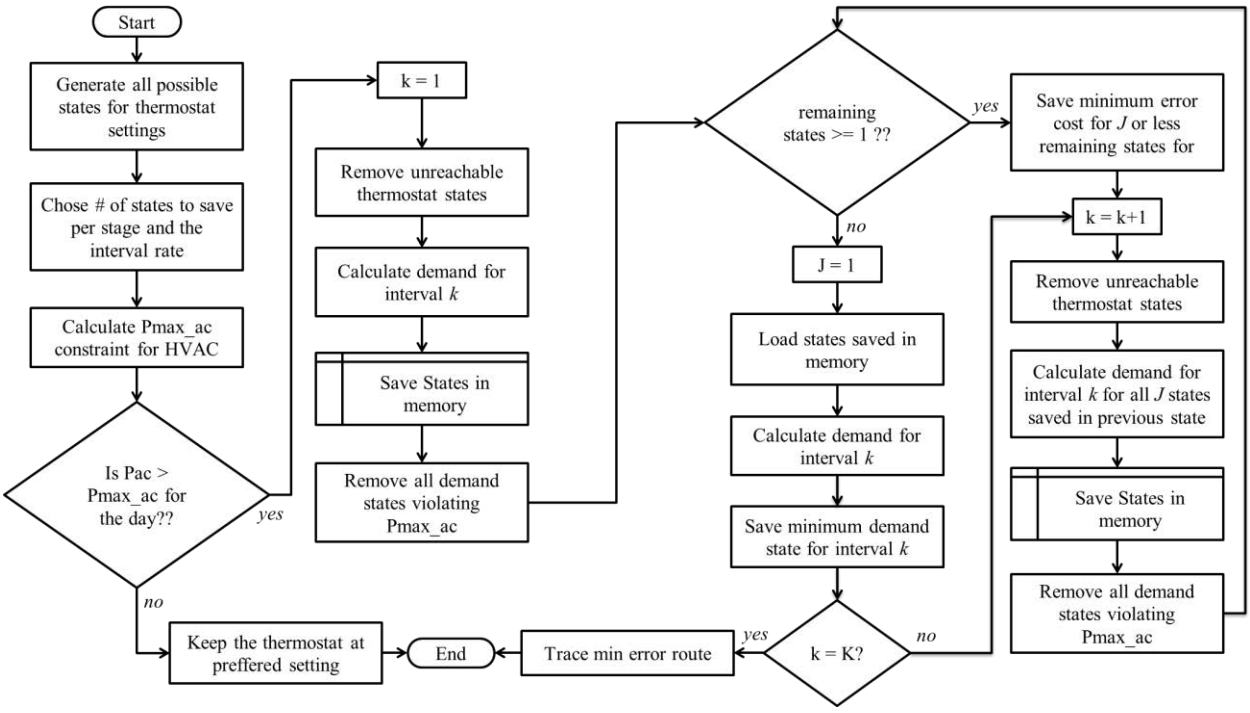


Fig. 17. Algorithm using forward dynamic programming

### 4.1 Simulation Procedure:

For simulation purpose, the residential load profiles were generated for five houses. Each house is assumed to have best insulation and same HVAC units as the all houses are considered of same size. The transformer is assumed to serve only these five houses. Since the HVAC parameters were tuned to perform as design day, choosing a house size is not significant anymore.

The per hour price signal for May 1$^{st}$ to August 31$^{st}$, 2012 from ComEd Illinois [35] was used in this work. Fig. 18 represents daily price signal averaged for the entire 123 days. Notice that the maximum average value is approximately 5.5 cents.

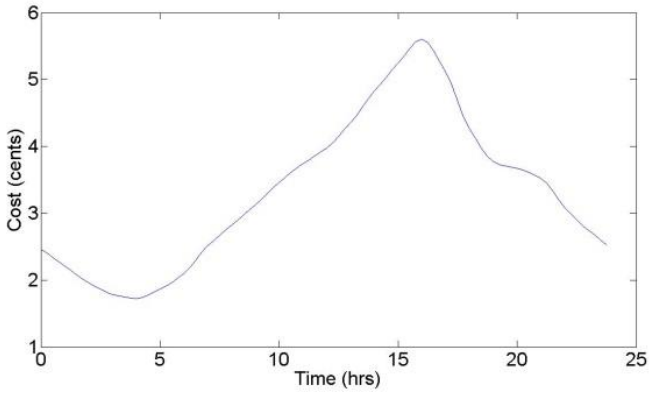


Fig. 18. Average price signal for 123 days

Fig. 19 represents histogram of the price signal and it is obvious from the histogram that very rarely the cost goes beyond 4 cents. This information was utilized to set inequality $p>4$ for the power constraint signal function. The different colors represent days.

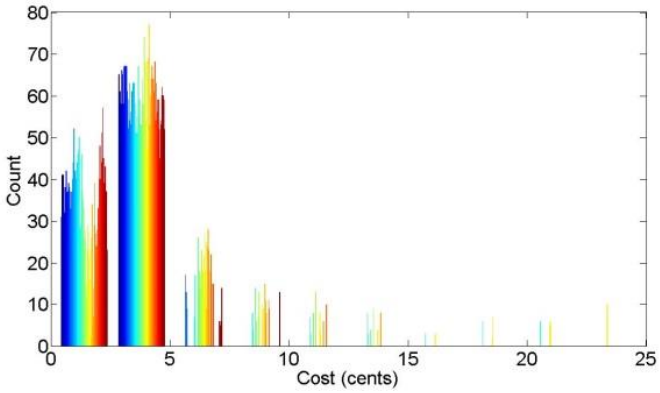


Fig. 19. Histogram of the price signal

A simple function for constraint signal is then written as follows,

$$P_i = \begin{cases} PT, & 0 \le p \le 2 \\ 0.9 \cdot PT, & 2 < p \le 2.5 \\ 0.8 \cdot PT, & 2.5 < p \le 3 \\ 0.7 \cdot PT, & 3 < p \le 3.5 \\ 0.6 \cdot PT, & 3.5 < p \le 4 \\ 0.5 \cdot PT, & p > 4 \end{cases} \tag{18}$$

where, $PT = 15$ kVA is Transformer's rating, $p$ is cost in cents.

As only air conditioning load is being controlled, therefore, the power constraint *Pmax_ac* for air conditioning load can be calculated by,

$$P_{\max_ac}(k) = P_{\max}(k) - AL(k) \tag{19}$$

Since we have tuned our ETP model parameters for Wichita-KS, weather data for the same location was downloaded for the same summer duration as that for the price signal, from [36]. Average temperature with standard deviations is shown in Fig. 20.

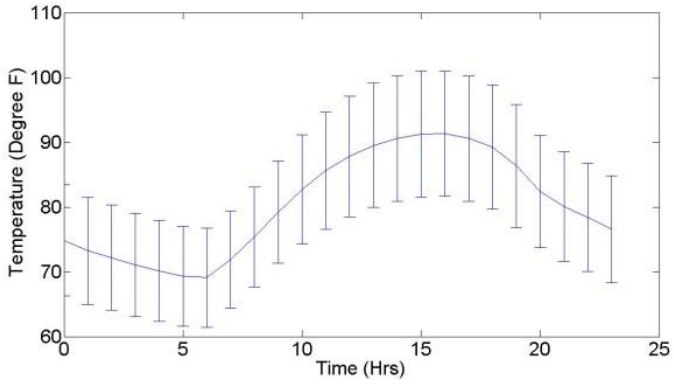


Fig. 20. Average outdoor temperature of 123 days with standard deviation bars

Another challenge was to choose number of states to be saved per stage (succeeding interval) for the program. Table III represents the effect of number of users and steps on the possible combinations of states for 60 minute control rate.

**Table III: Effect of number of users and steps on computation requirements**

| | | **N** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Steps** | **3** | | 3 | 9 | 27 | 81 | 243 | 729 | 2187 | 6561 | 19683 | 59049 |
| | **5** | | 5 | 25 | 125 | 625 | 3125 | 15625 | 78125 | 390625 | 1953125 | 9765625 |
| | **7** | | 7 | 49 | 343 | 2401 | 16807 | 117649 | 823543 | 5764801 | 40353607 | 282475249 |

Notice the significance of increasing the number of houses (equal to number of HVAC units) *N* or number of *steps*; increasing either of them will increase the amount of computation required to solve the problem and will ultimately require more sophisticated system. Fortunately, in dynamic programming a constrained system can help avoid some portion of states. However,

that portion can or cannot be significant help, thus requires some basic analysis to find out enough number of states to be saved for each control rate and its respective possible steps.

An initial test with the design outdoor temperature of 98 $^0$F and 74 $^0$F thermostat setting was run to target this problem. All the HVAC units were allowed full deviation range i.e. 69-79 $^0$F, and were assumed to be having same power rating i.e. 3kW as well as the starting point temperature. We chose 3kW power rating for each HVAC unit so that the maximum coincident demand matches 15kW which is the power rating of the transformer supplying these loads. With only HVAC load in system, the simulation was run for each control frequency to acquire maximum achievable peak reduction and PAR reduction with all states saved per stage of the forward dynamic algorithm. Table IV presents the results of the initial test.

**Table IV: Initial analysis results to see the effect of reducing the number of saved states**

| Control Frequency | Possible Steps | Percentage Reduction | 0.1 | 1 | 5 | 10 | 100 |
|---|---|---|---|---|---|---|---|
| **60** | 7 | PAR | 9.99 | **9.76** | - | - | 9.99 |
| | | Peak Demand | 31.03 | **31.03** | - | - | 31.03 |
| **60** | 5 | PAR | 7.45 | **9.8** | - | - | 9.99 |
| | | Peak Demand | 29.66 | **31.03** | - | - | 31.03 |
| **60** | 3 | PAR | | 8.96 | **9.93** | 9.93 | 10.12 |
| | | Peak Demand | | 29.66 | **29.66** | - | 29.66 |
| **30** | 5 | PAR | 31.6 | **42.77** | - | - | 42.89 |
| | | Peak Demand | 48.7 | **56.52** | - | - | 56.52 |
| **30** | 3 | PAR | | 31.15 | **42.02** | 42.46 | 42.79 |
| | | Peak Demand | | 47.83 | **55.65** | - | 55.65 |
| **15** | 3 | PAR | | 37.54 | **53.05** | 53.83 | 54.2 |
| | | Peak Demand | | 53.33 | **64** | - | 64 |

From the table, using the percentage of steps that give closest results to the column for 100% states saved, the number of states to be saved to get reasonable results can be calculated using,

$$sts = \frac{ps * steps^{N}}{100} \tag{20}$$

where,

*sts* is states to save and *ps* is percentage of states chosen from the Table IV. Since number of states cannot be in fractions, *sts* is rounded to the nearest integer.

With the respective *sts,* the algorithm is then run for 500 iterations, for $N$=5 users. The results are discussed in next chapter.

# CHAPTER 5

# RESULTS

All the results are within 95% confidence interval. In Fig. 21, a comparison of different steps for the 30 minute control signal is shown representing benefits to the utility. Fig. 21(a) and (b) represent percentage reduction in total number of $P_{max}$ violations and the violation energy, before and after sccheduling. It should be noted that the higher steps did not imprive the performance. Similar is the case with Fig. 22(a) which shows peak reduction, infact notice that the maximum duration of sustained violation was degraded as can be seen in Fig. 22(b). From consumer point of view, the average total deviation from the setpoint (Fig. 23(a)) throughout the day was not much improved, however the maximum duration of deviation from preferred thermostat settings is reduced as is reflected by the mean and standard deviation values in 23(b).

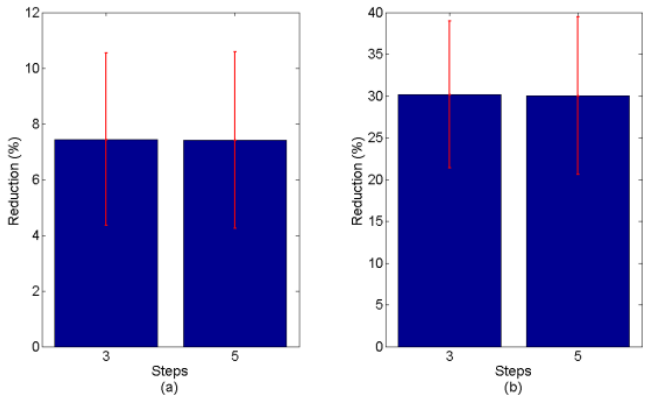


Fig. 21. (a) Percentage reduction in per minute violation count, (b) Percentage reduction in violation energy

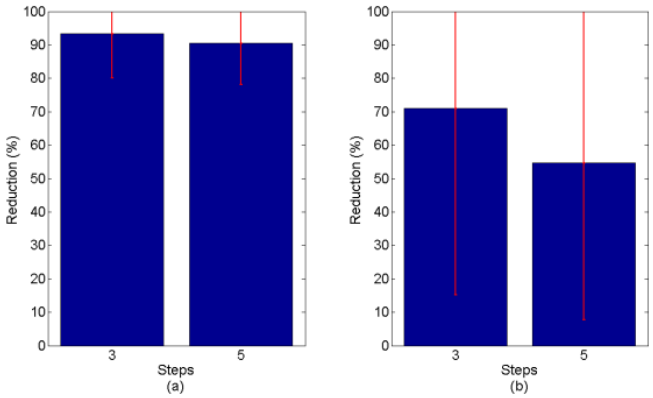


Fig. 22. (a) Percentage reduction in peak demand, (b) Percentage reduction in maximum duration of sustained violation

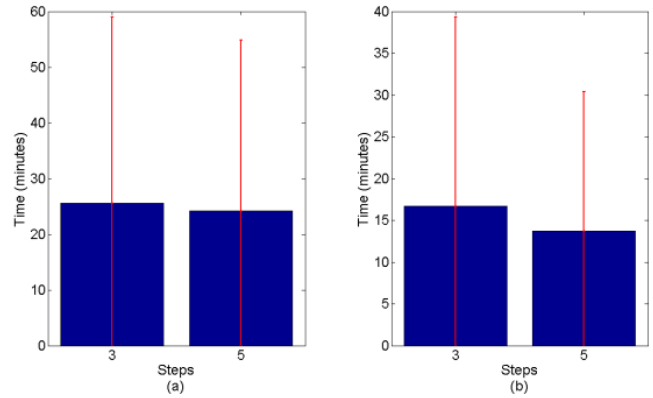


Fig. 23. (a) Total deviation from preferred thermostat settings in minutes, (b) Maximum continuous deviation from preferred thermostat settings in minutes

Fig. 24, 25 and 26 represent similar plots for the 60 minute control with 3, 5 and 7 steps possible, as discussed earlier. Although there can be seen some benefit in chosing more steps per stage, the overall reduction achieved in terms of the violation energy is very small, see Fig 24(b). Also, the violations in any form that can be seen by the constraint signal naturally reduced due to the averaging for a much wider time slot. The standard deviation bars below zero represent that in some cases the violations were actually increased after scheduling. This is due to the lost of finer control when 60 minute control signal is chosen. Also, there wasn't much achieved in peak reduction, neither in suststained violation reduction when more steps were chosen, in fact the

performance was actually degraded. Finally, nothing significant was achieved from the consumer point of view as well as can be seen from Fig. 26(a) and (b).

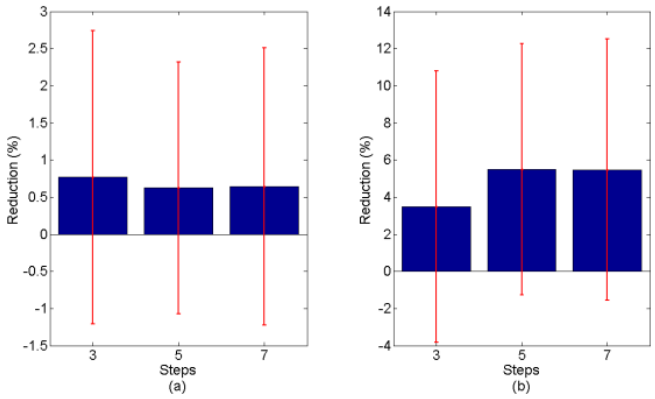


Fig. 24. (a) Percentage reduction in per minute violation count, (b) Percentage reduction in violation energy

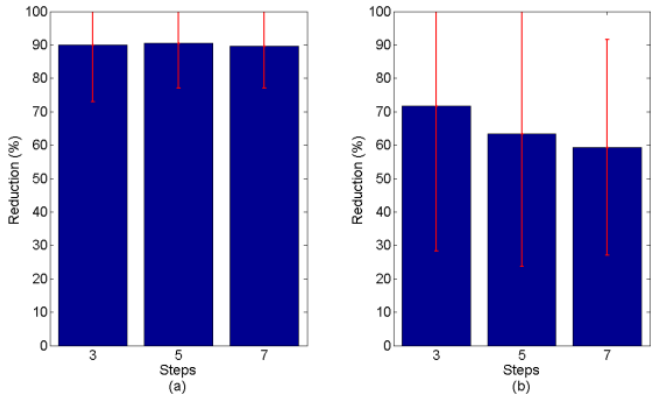


Fig. 25. (a) Percentage reduction in peak demand, (b) Percentage reduction in maximum duration of sustained violation

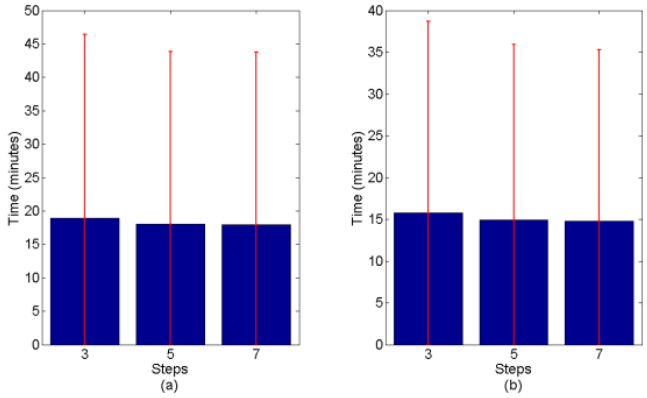


Fig. 26. (a) Total deviation from preferred thermostat settings, (b) Maximum continuous deviation from preferred thermostat settings

Since the 15 minute control can not take more than 3 steps, Fig. 27, 28 and 29 compares all three control sampling rates with 3 steps. It is very obvious from Fig. 27(a) and 27(b) that 15 minute control did best, however, things changed when reduction in peak demand and maximum sustained violations were compared. Notice in Fig. 28(a) and (b) that the percentage peak reduction achieved for each control signal is very similar and may not help much as a decision making factor but the maximum duration of sustained violation is improved a little bit. This is due to the control available for wider time slot in case of 30 and 60 minutes sampling i.e. once a decission is made about the entire time slot, it is for the entire duration of that wider slot, hence on average it performs better. The benefits to the consumer are sorted in Fig. 29. As can be seen in Fig. 29(a), 60 minute control did best in terms of deviation from preferred thermostat settings with mean value of 10 minutes lower than 15 minute control, however, the maximum continuous deviation from the preferred setting did not change significantly.

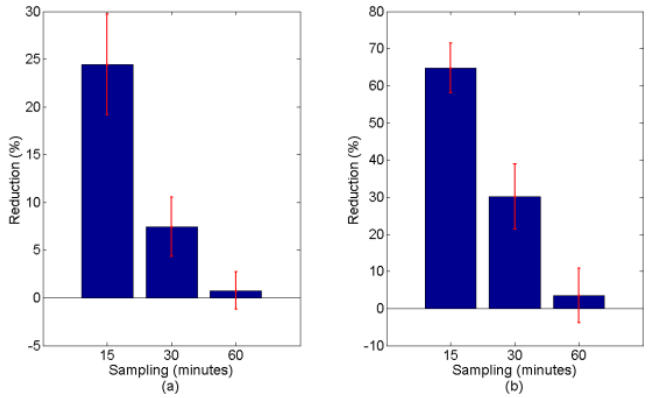


Fig. 27. (a) Percentage reduction in per minute violation count, (b) Percentage reduction in violation energy

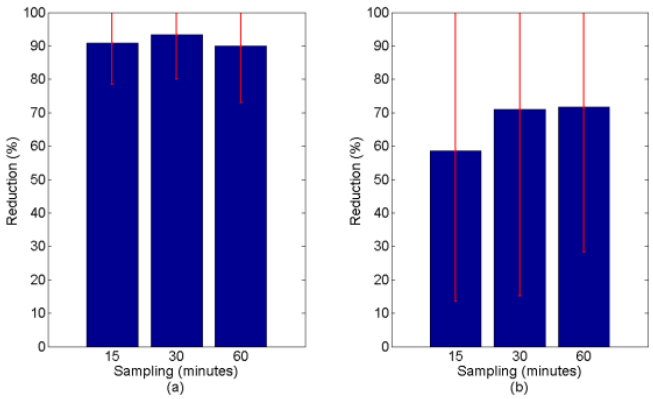


Fig. 28. (a) Percentage reduction in peak demand, (b) Percentage reduction in maximum duration of sustained violation

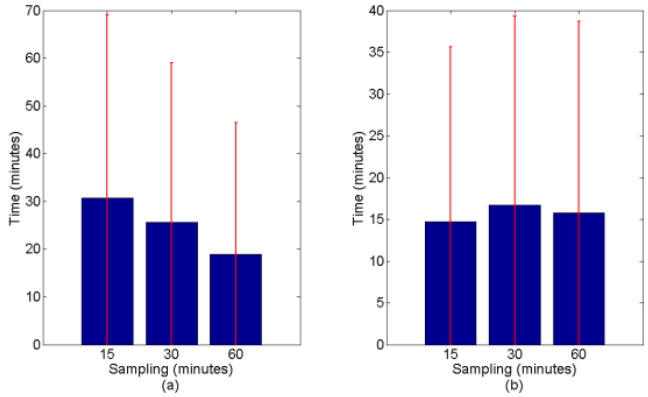


Fig. 29. (a) Total deviation from preferred thermostat settings, (b) Maximum continuous deviation from preferred thermostat settings

# CHAPTER 6

# CONCLUSION AND FUTURE WORK

A forward dynamic programming based algorithm is developed in order to analyze the impact of different control frequencies i.e. 15, 30 and 60 minute on both the consumer and the utility. The three control frequencies were compared to summarize tradeoffs when moving from one control frequency to the other. Each control frequency was also analyzed for its limits in terms of number of steps that can be taken while changing the thermostat settings.

Although the benefits of choosing more steps for the respective control frequency were there, the specific cases where 30 and 60 minute control did better than 15 minute control frequency (like percentage reduction in sustained violation and total duration of violation), there wasn't any benefit in choosing higher number of steps. Thus, it can be concluded that it is always feasible to choose lower number of steps and lower control frequency as long as one is dealing with the analyzed parameters.

A major factor that comes in the way of day-ahead scheduling is the price variations. However, if the constraint signal from the utility is sent in order to match a certain profile and thus promising the price signal, the variations in price signal can be reduced as is obvious from the peak reduction and violation energy reduction results. This will also help in forecasting the price signal more accurately. Moreover, while the reduction in peak demand would help in increasing life expectancy of transformers, the reduction in energy usage at the time of violation will help in reducing reserve capacity requirements.

One major concern while using dynamic programing is the number of possible combinations (states) per stage which increases with the number of users as was shown in Table III. For instance, for 10 units to be scheduled in a system there are 59,000 states. In worst case,

where all the consumers are willing to let the thermostat deviate at maximum from the preferred thermostat settings, the system will have to solve the scheduling problem with most number of states. Thus a more constrained system poses computationally less burden on the system. Also, the number of states to be saved per stage gives reasonable results even when a small portion of maximum possible states is saved.

As a future work, the algorithm can be improved to serve as an on demand scheduler i.e. responding to instantaneous needs in order to achieve peak reduction. Currently, the algorithm is only able solve in one go; by going back and choosing different paths when the solution is not found can help in finding better solution. Furthermore, analyses of a complete system, i.e. with heating system as well as electric vehicles can be done as well, to realize the impact throughout the year for an entire feeder serving many transformers. The impact on transformer and other equipment's life expectancy can also be analyzed.

One of the limitations of this work is that the $P_{max}$ constraint signal chosen for each control signal is same and naturally, unable to see majority of the violations for higher control frequencies. This can be taken as a future work to enforce different constraint signals for each control frequency and then analyze the system again. Also, the analysis can be further improved by choosing respective range parameters for the ETP model which would definitely require a faster algorithm as the range for each parameter will be varied and will need more iteration to conclude the results statistically.

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# REFERENCES


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