Spring 5-1-2013

Energy-Efficient Smart Home System: Optimization of Residential Electricity Load Management System

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Energy-Efficient Smart Home System: Optimization of Residential Electricity Load Management System

A Capstone Project Submitted in Partial Fulfillment of the Requirements of the Renée Crown University Honors Program at Syracuse University

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May 2013

Honors Capstone Project in Electrical Engineering

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Abstract

In this project, an algorithm for electrical load management in a hypothetical household setting is proposed, developed and simulated. There are two main goals for the algorithm; firstly, to minimize the total electricity cost when a variable pricing model is applied; secondly, to flatten the demand curve over 24 hours, which, when applied to real-life settings, will minimize investment costs for the utilities – including building more generation plants and transmission lines – as well as the total bill for customers. To simulate the algorithm, mathematical models for appliances are developed based on typical usage and operation patterns.

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Acknowledgements

I would like to express the deepest appreciation to Dr. Tomislav Bujanovic, for his constant encouragement and support throughout this project. His guidance and help has made possible for this project to come into fruition.

I am hugely indebted to Dr. Michael Jefferies for his questions that needed to be asked, and his insights that this project was in need. I am thankful for his effort to help.

In addition, a thank you to Dr. Ghosh, who first introduced me to the topic of Smart Grid.

I thank Mohammad Nikkhah Mojdehi for his persistent help, and teaching me how to perform optimization: a critical component of this project.

I. Introduction

Electricity demand continues to rise. The Annual Energy Outlook, a report by the U.S. Energy Information Administration, predicts that electricity demand would grow by 22 percent from 3,877 billion kilowatt-hours in 2010 to 4,716 billion kilowatt-hours in 2035 [1]. The growth includes both increases in residential buildings and commercial buildings, which account for over 75% of electricity consumption in the United States [2]. As resources are limited and with current technologies, it is much more expensive to produce energy using renewable sources than using hydrocarbons, it is increasingly desirable to develop and implement energy management technologies in buildings that would help reduce demand.

Smart Home denotes a home energy management system that can be implemented into Smart Grid, a new kind of electric grid that allows two-way communication between the electricity provider and its customers. Electric utilities as well as the government in the United States are continuously making investments in creating Smart Home systems that will lower energy consumption as well as flatten the demand curve [4]. Flattening demand, also called peak shaving, implies reducing the differences between the peaks and troughs in electricity usage [5]. In typical households, higher electricity demand during a 24-hour period falls on certain times of day, which eventually results in a demand pattern with peaky behavior, as presented in Figure 1 below.

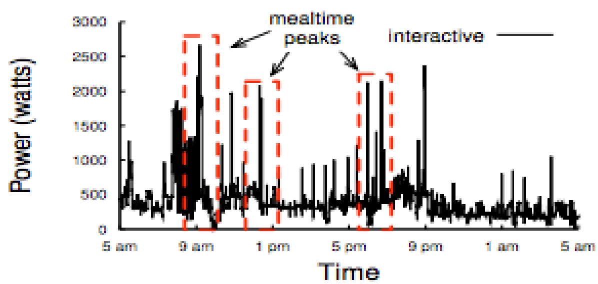


Figure 1. Typical energy demand in household (Source: SmartCap: Flattening Peak Electricity Demand in Smart Homes)

Lowering the highest demand values of power consumption is beneficial because it improves efficiency in generation and transmission of electricity. Furthermore, the higher the maximum amount of electricity in demand, the more costly it is for the utilities to meet the needs, such as added generation, transmission lines, substations, et cetera. In the future, more utilities will charge for electricity variably depending on the demand model, rather than charging the same amount for each time of day [5], [6]: such a model is called a Time-Of-Use (TOU) pricing model. Within this setting, flattening the demand curve will be beneficial for the customers as well – when the power consumption during peak times is reduced, the lower the energy bill will be.

In this project, an algorithm to optimize the total electricity bill is presented and its performance is demonstrated. The algorithm adjusts the power consumption for each time interval as well as operation starting time and ending time for each electrical appliance, or 'load'. The household loads are divided into few different classes by their operation patterns – each category is explained in more details in Sections II and III of this paper. It is assumed that there is a device that enables the two functions of shifting loads and varying the power consumption for each load, making the load "smart". The system model from the paper [7] – "Residential Electricity Load Scheduling for Multi-Class Appliances with Time-of-Use Pricing," written by Jang-Won Lee and Du-Han Lee – is adopted and the corresponding algorithm is developed. The testing scenarios are elaborated in this project; rather than simply setting up thresholds for the parameters for appliances in each class by choosing random integers, specific operation patterns are incorporated for simulations. Also, households are divided into two types in an attempt to create more realistic settings for simulations. MATLAB is utilized throughout the simulations in order to test the algorithm suggested by the authors in [7] and the author of this paper.

For the evaluation, the total electricity demand curves as well as the price curves, without optimization and with optimization, are compared and discussed in Sections IV and V. Also, potential benefits of implementation of the algorithm are explained. Recommended future improvements are discussed in Section VI.

II. Background Information and Proposed Approach

There is a large amount of literature on electricity demand response [9], where each paper evaluates various aspects of the topic that can be employed in designs of Smart Home systems. In this project, concept and ideas from previous works [5], [7], [9] are adapted and used in order for the author to develop a system model as well as an algorithm to achieve the goals of this project: 1) to optimize the power consumption vector for each appliance to minimize the total cost and 2) to flatten the demand.

In [7], the authors divide electrical appliances to four categories: set of appliances with elastic energy consumption without storage, set of appliances with elastic energy consumption with storage, set of appliances with non-elastic and interruptible energy consumption, and set of appliances with non-elastic and non-interruptible energy consumption. In this project, the first and the fourth categories and their respective mathematical models are adopted.

In [5], the authors define two categories of appliances: background loads and interactive loads. Background loads are appliances that home occupants do not directly control, but only passively observe their behavior; examples include refrigerators, dehumidifiers, and A/Cs. Interactive loads are those that home occupants directly control; examples include lights, TVs, computers, microwaves and vacuums. Background loads have more flexibility to be re-scheduled and turned on and off than interactive loads.

In this paper, home appliances are divided into three categories: background loads, schedulable interactive loads and not schedulable (or "unschedulable") interactive loads. The difference of these categories from categories defined in [7] lies in the fact that batteries are not considered. Terminologies are adopted from [5], yet this paper assumes that there are certain appliances that can be re-scheduled, such as washers. Companies like GE, LG and Samsung are investing in developing and implementing functions that will enable re-scheduling such as a delay function in washers. Unschedulable interactive loads include computers, microwave, TV and telephone: appliances that have a visible impact when there is a power draw and disrupt users' comfort.

The algorithm aims to optimize the power demand for each hour-long time interval so that the total electricity the customer has to pay for will be minimized. Also, once the power consumption vector is obtained, the algorithm goes on to find the peak times and decides whether or not to disable background circuits.

In this paper, the system model is defined and simulated for two types of household settings; for the first type, the home occupants are assumed to stay at home the entire day; for the second type, the occupants are assumed to leave the house during the day for work at 9 a.m. and get back at 5 p.m. The algorithm generates comparison graphs for observation of different settings and different algorithms.

III. System Model and Classes of Appliances

This project attempts to simulate a mathematical model of a household that reflects typical usage patterns of electricity in real-life. Here, system model and categorizations of appliances proposed in [7] are adapted. It is assumed that there is a controller that has the ability to schedule the starting and ending time of operation as well as to regulate the amount of energy consumption of each appliance at each sub-interval.

A. System Model

A residence with a set of *A* electrical appliances is considered. Energy consumption vector of each appliance *a* is defined as

$$x_a = [\, x_a^1, x_a^2, \dots, x_a^T]$$

where x_a^t is the amount of energy consumption of appliance *a* during sub-interval *t* among *T* sub-intervals. In this paper, it is assumed that each appliance *a* has its schedulable interval $[S_a, F_a]$ only during which it can be scheduled. Each sub-interval is an hour long. The length of this interval is defined as

$$L_a = F_a - S_a + 1.$$

For each appliance *a*, it is assumed that there are maximum and minimum values for energy consumption, in each sub-interval t:

$$x_a^{min} \leq x_a^t \leq x_a^{max}$$

A Time-of-Use (TOU) model is applied. The unit price for energy for each sub-interval *t* is denoted as λ_t. All λ_t's for the entire scheduling interval are assumed to be known in advance. Equation of the total energy cost for the residence is as follows.

$$C_T(x) = \sum_{t=1}^{T} \lambda_t * \sum_{a \in A} x_a^t$$

The TOU model based on electricity price per hour provided by NYISO is as shown below.

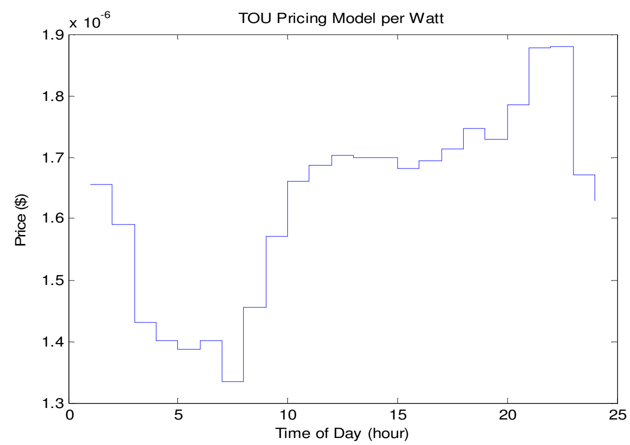


Figure 2. TOU Price of Electricity. Source: NYISO

The day-ahead locational based marginal pricing on May 5th, provided by NYISO's website [10], is used; the hourly price is multiplied by 5 for the price to match the current average price, which is about 15 cents per kWh [11]. The price graph reflects the common electricity demand pattern; price for peak demand times are higher.

B. Class of Appliances

Each class of appliances is characterized by a utility function U, and constraints on the consumption vector. The constraint function for each class is adapted from [7], too.

- Background Loads: This class includes appliances such as air conditioners, heaters, refrigerators and light bulbs with controllable brightness. Energy consumption for this set of appliances can be adjusted at each sub-interval, without interfering with the user's lifestyle and welfare. Authors of [7] use a constraint function based on what they call "performance," which is equivalent to "satisfaction of a user." Performance is determined by a utility function for each appliance a, which is denoted as $U_a^t(x_a^t)$, where the appliance consumes x_a^t units of energy at sub-interval t. In this paper, the utility function is assumed to be an increasing and strictly concave function. Constraint is decided by taking the average of performance of each hour, and setting up boundaries for the power demand at each sub-interval. Authors of [7] set up a requirement of the minimum threshold: the average performance of appliance a should be higher than or equal to β_a:

$$\frac{1}{L_a}\sum_{t=1}^{T} U_t(x_a^t) \geq \beta_a\,, \forall a \in A_1$$

- The appliances with energy storage are not discussed in this work.

- Schedulable Interactive Loads: The third class includes appliances that are interactive, yet schedulable for throughout the day. Appliances such as washer and dishwasher belong to this class. The requirement is defined for the total energy consumption of appliance a to be higher than or equal to its minimum threshold β_a:

$$\sum_{t=S_a}^{F_a} x_a^t \geq \beta_a, \forall a \in A_3$$

- Unschedulable Interactive Loads: The fourth class includes appliances that are interactive, and cannot be re-scheduled. The user decides when to start and end the operation of each device, as well as the amount of power consumption. TV, microwave, coffee maker, and the computer belong to this class.

IV. Simulations

In this section, the setup for simulations and definitions of each appliance is provided. The utility functions are adapted from [7] while the simulation strategies and definitions of appliances are adopted and modified from [8].

A. Utility Function

For the background loads and schedulable interactive loads, a simple increasing and strictly concave function is used as a utility function:

$$U_a(x) = \log(x + 1), a \in A$$

B. Constraints

For the background loads, the minimum performance threshold β_a is determined using the equation

$$\beta_a = L_a \times U_a(x_a^{max}).$$

For the schedulable interactive loads, β_a is determined using the equation

$$\beta_a = L_a \times x_a^{max}.$$

C. Simulation Setup

Before modifying simulation set-up suggested by authors of [7], this paper performs simulations as done in [7].

To evaluate the efficiency of the algorithm, performance of the unscheduled case is compared to the scheduled case. It is assumed that for the unscheduled case, once an application is on, it always consumes the energy with its maximum power limit until its performance threshold is satisfied. For each class, 20 appliances for each class are considered, and therefore 40 appliances in total are simulated.

a. Parameters Set-Up

The parameters for each appliance are generated randomly. The setup for each parameter is directly adapted from [7]:

- starting time (S_a): with a uniform distribution between sub-intervals 1 and 24;
- finishing time (F_a): with a uniform distribution between sub-intervals S_a and 24;
- maximum power consumption (x_a^{max}): with a uniform distribution between 0 Watt and 1500 Watt;

- threshold (β_a): with a uniform distribution between 0 and $L_a \times U_t(x_a^t)$ for appliance a that are background loads and between 0 Watt and $L_a \times x_a^{max}$ Watt for appliance a that are schedulable interactive loads.

C. Block Diagram of the Algorithm

- For simulation of the system model that is adapted from [7]:

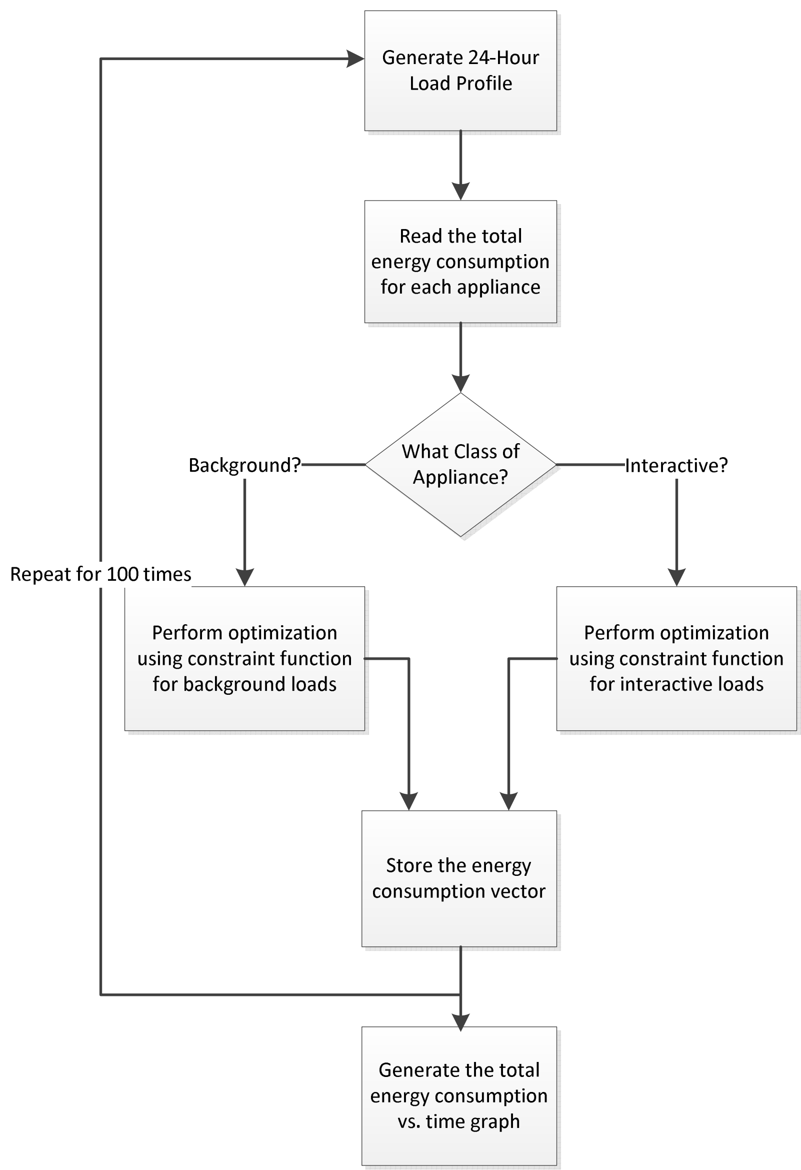


Figure 3. Block Diagram of Algorithm: System Model Adapted from [7]

- For simulation of the system model of this paper:

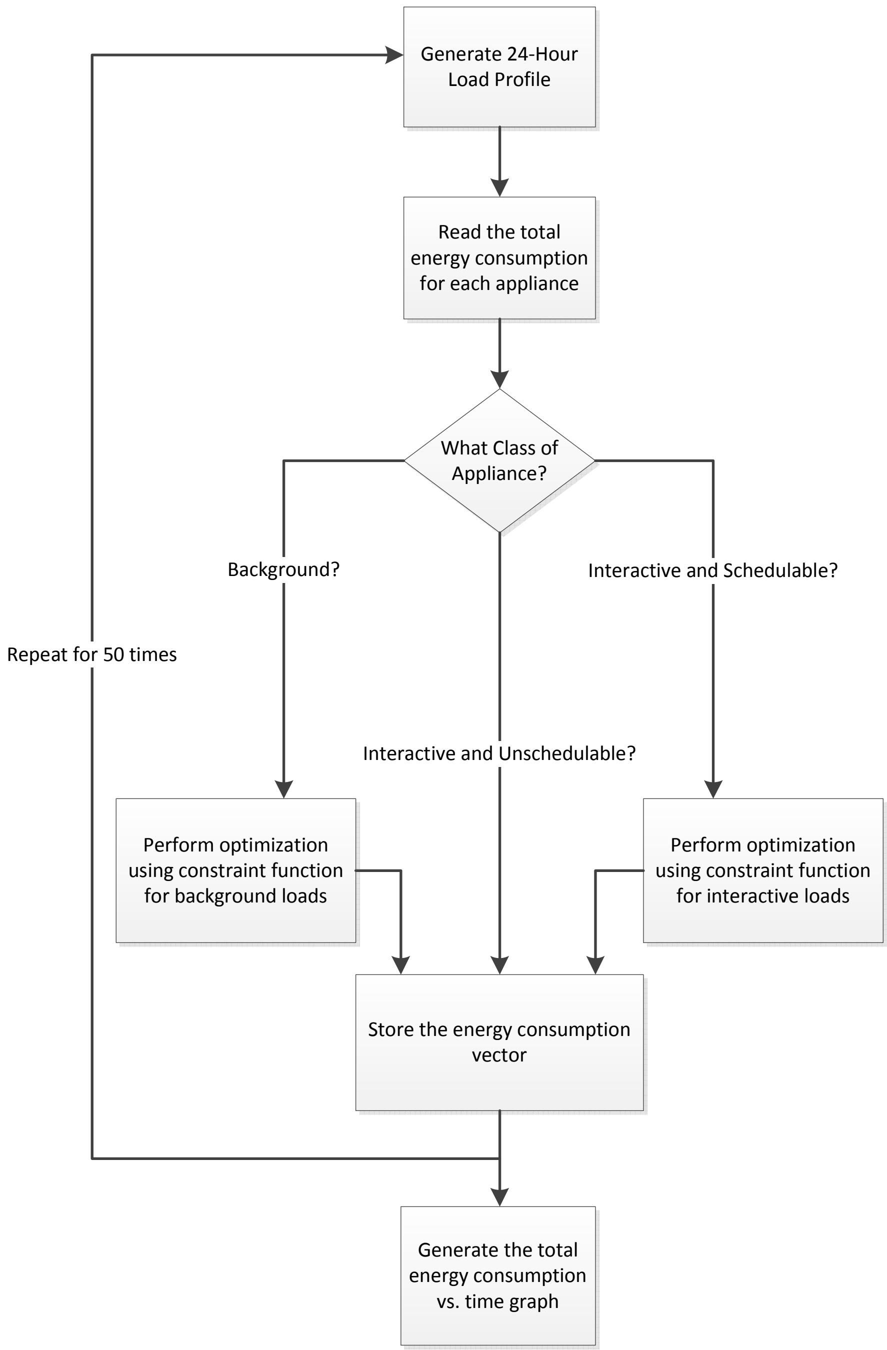


Figure 4. Block Diagram for Simulation of System Model Proposed by this Project.

D. Results for System Model in [7]

Simulation is run 100 times and average of performances at each sub-interval and the average total electricity bill are taken. The m files used for simulating the system can be found in Appendix 1.

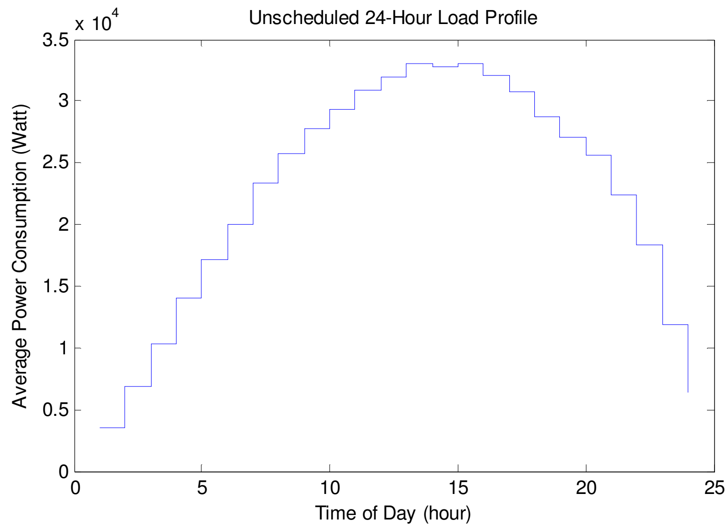


Figure 5. Unscheduled 24-Hour Load Profile

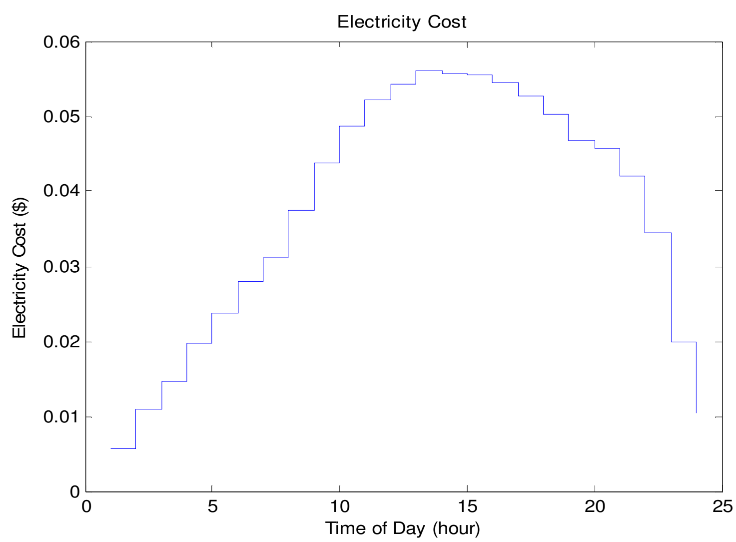


Figure 6. Average Electricity Cost per Hour

The average of total electricity bill for 100 unscheduled 24-hour load profiles for one day came out to be 0.8941$. This means that if this scenario was simulated for 31 days, the average electricity bill for each household would be $27.72.

The optimized power consumption vector with the algorithm the authors of [9] suggest is as follows.

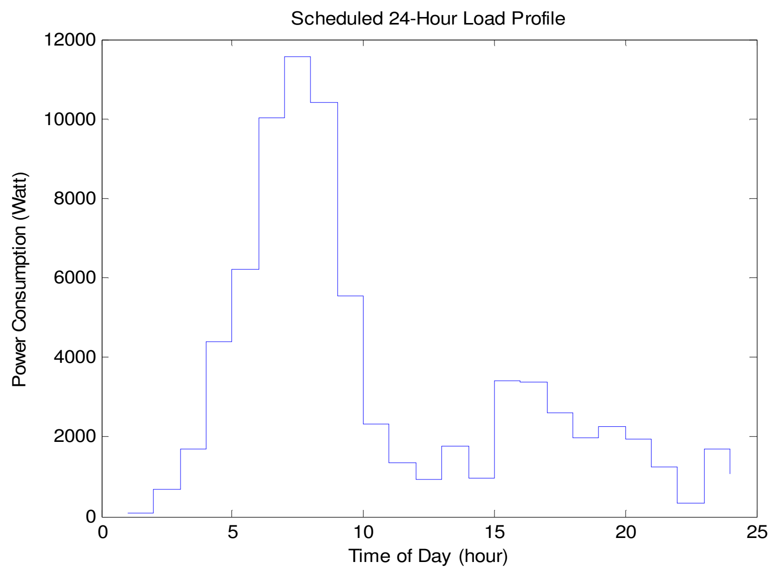


Figure 7. Scheduled 24-Hour Load Profile for Each Household

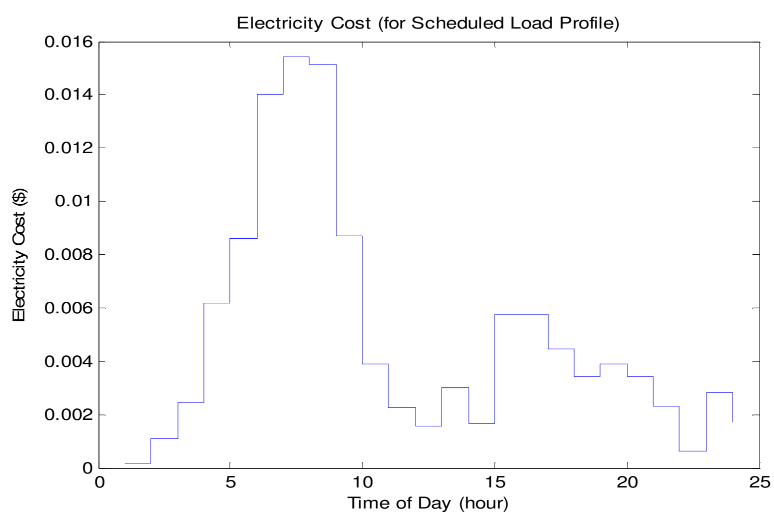


Figure 8. Optimized Electricity Cost for Each Hour

The total electricity bill for the unscheduled 24-hour load profile for one day came out to be 0.1184$. This means that if this scenario was simulated for 31 days, the electricity bill would be $3.67.

For comparison, the load profile of the scheduled case is superimposed on top of the unscheduled case as follows. The price curve (in dashes) was re-scaled and modified for visual comparison.

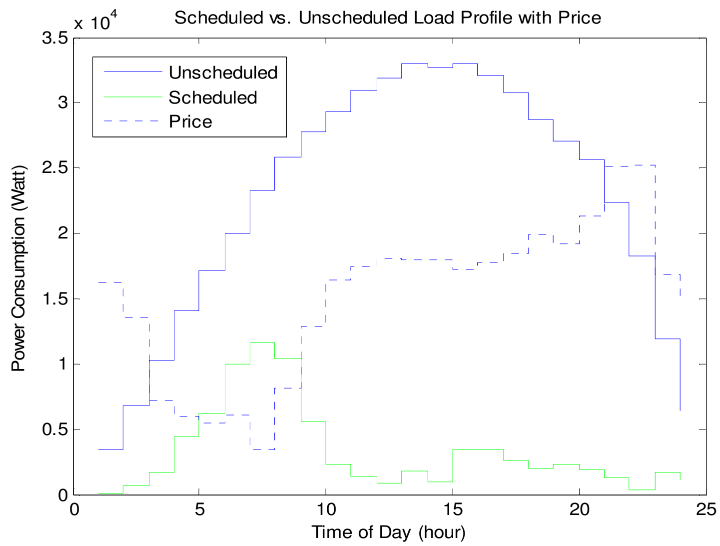


Figure 9. Load Profiles

	Unscheduled ($)	Scheduled ($)	Saving Rates (%)
1 Day	0.8941	0.1184	17.7
31 Days	27.72	3.67	86.76

Table 1. Comparison of the Electricity Bill with the Unscheduled Case.

The results resemble that of [7] that as follows:

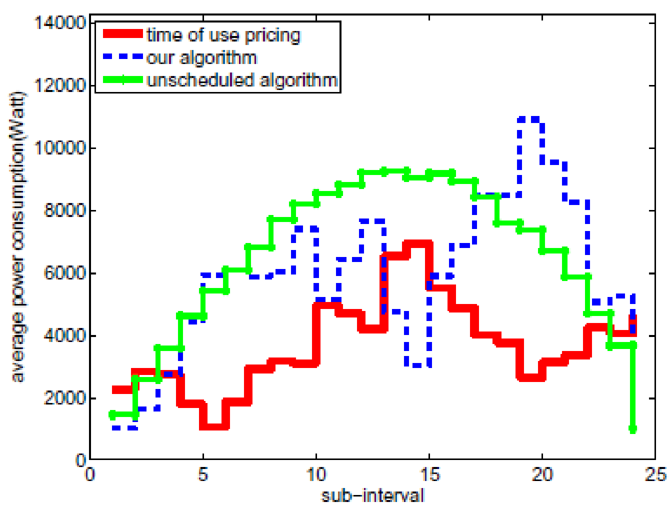


Figure 10: Source: N. Li, L. Chen, S. H. Low. Optimal Demand Response Based on Utility Maximization in Power Networks. Engineering & Applied Science Division, California Institute of Technology.

COMPARISON OF THE ELECTRICITY BILL WITH THE UNSCHEDULED CASE.

appliance class	unscheduled	scheduled	saving rates (%)
set A_{EwoS}	18398	11152	40.1
set A_{EwS}	18138	16720	7.7
set A_{nEI}	12637	11199	11.4
set A_{nEnI}	12613	11806	6.8
total	61786	50877	17.7

Table 1: Source: N. Li, L. Chen, S. H. Low. Optimal Demand Response Based on Utility Maximization in Power Networks. Engineering & Applied Science Division, California Institute of Technology.

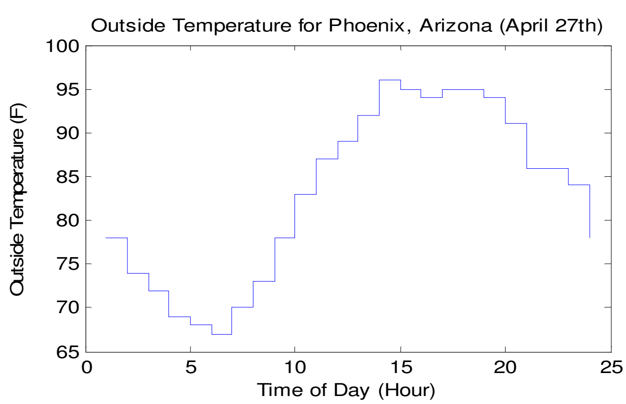
Both of the graphs of power consumption for unscheduled cases have a similar shape. Also, it can be observed that for both simulations, power consumption is lower for times when the price is high and higher for times when the price is low. Saving rate was found out to be significantly higher for the results in this project than results in [7]: 86.76% versus 17.7%. The differences between results in [7] and in this project are assumed to stem from the absence of batteries in simulations done in this project, as well as different daily price data.

E. Updated Simulation Setup

Results for Authors of [8] simulate both unscheduled and scheduled scenarios with randomized parameters for 40 appliances for 100 times. This project assumes two categories of household; for the first type, the home occupants are assumed to stay at home the entire day; for the second type, the occupants are assumed to leave the house during the day for work at 9 a.m. and get back at 5 p.m.

Instead of assuming 20 appliances for the background loads, air conditioner, refrigerator and light fixtures with controllable brightness are considered as background loads (BG). Instead of assuming 20 appliances for the interactive loads, the author assumes lights without controllable brightness and washer as schedulable interactive loads (SIA), and entertainment station as an unschedulable interactive load (USIA). Parameters for each appliance are as follows.

1. Air Conditioner (BG): Operations of air conditioners are determined by factors such as the difference between outside temperature and inside temperature. For simplicity, this project assumes that the home occupants will turn on the air conditioner during times when they are in the house and the outside temperature goes above a threshold. Hourly temperature data for April 27th in Phoenix, Arizona are considered [12].



temperature = [78 74 72 69 68 67 70 73 78 83 87 89 92 96 95 94 95 95 94 91 86 86 84 78]

Figure 11: Outside Tempearture

The project assumes that a home occupant will turn on the air conditioner when s/he is present in the house and the temperature exceeds 78F. The minimum energy consumption is 1000 Wh, and maximum 4000 Wh.

2. Refrigerator (BG): The fridge is on throughout the day for both types of households, yet the times that the home occupants open the door varies, and so does the power consumption: the higher the number of times the occupant opens the door, the more power the appliance consumes. The appliance is assumed to automatically turn on for forty minutes and off for twenty minutes to maintain its internal temperature, and during the on period, has higher power consumption to compensate the increase of temperature due to occupants opening the door. The number of times of opening the door is randomized with normal distribution with a mean of 3 and standard deviation of 4/3. For the first type of household, the number of times is set up for all day. For the second type, the number of times of opening the door is randomized for only when the occupant is present in the house. The minimum energy demand is 150Wh, and with every opening of door, the minimum energy demand is increased by 20Wh.

3. Washer (SIA): It is assumed that washer will be used at least once in a day. For the first type of household, the home occupants operate the machine during the time they are awake: between 7am and 12pm. For the second type of household, the operation time lies between 5pm and 7am. It is assumed that there is an override switch that will let the user operate at his or her convenience, but they are not incorporated into the scenario. The minimum and maximum total energy demands are 1400 Wh and 2500 Wh, respectively. For optimization, it is assumed that the appliance has a delay function, which will automatically re-schedule the operation of the appliance to a low-price region during the entire day.

4. Light fixtures with controllable brightness (BG): The minimum and maximum energy consumptions are 0W and 400W. They are on when the occupants are awake and present in the house.

5. Light fixtures without controllable brightness (USIA): For the households of the first type, $x_{a,min}$ = 100Wh and $x_{a,max}$ = 200Wh. The available operation time starts at 10am and ends at 12am. For the ones of the second type the thresholds are the same as the first type and the operation starts at 5pm and ends at 12am. Power consumption vector is determined by randomly selecting values between the thresholds.

6. Entertainment station (USIA): For this set of appliances, maximum and minimum thresholds of energy consumption are as follows; for the households of the first type, $x_{a,min}$ = 0Wh and $x_{a,max}$ = 3500Wh and the operation time starts at 10am and ends at 12am; for the ones of the second type, the thresholds are the same and the operation starts at 7pm and ends at 12am.

F. Demand Response

Using the parameters for each appliance, demand response is computed. m files of objective function and constraint functions as well as commands for optimization for each appliance are to be found in Appendix 2. To test all the systems, download all m files in Appendix 1 and 2 and simply type in 'main' and follow instructions.

Assuming that for the unscheduled case all appliances consume its maximum power consumption threshold when they are on, the following power consumption graph was generated. Both types of households are simulated for 50 times, and then the average is taken for the power consumption for each time interval.

Optimization algorithm is simulated for one time, then 50 times, and then the average for the power consumption vector is taken.

Results of simulations are as follows.

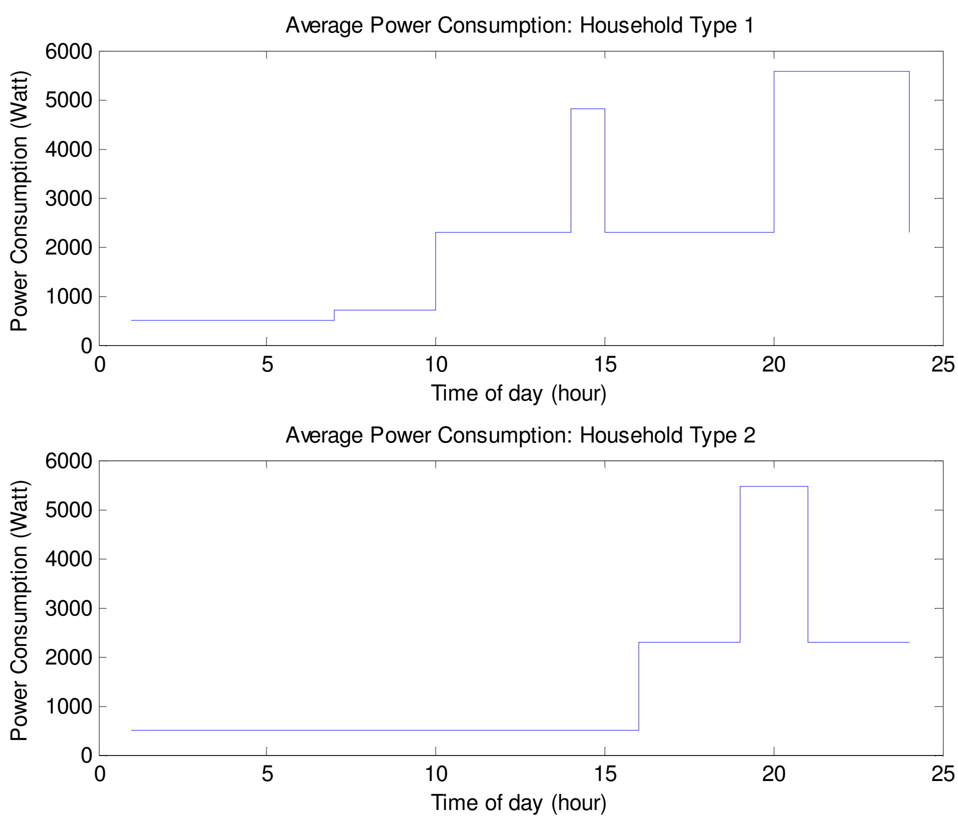


Figure 12. Load Profile of Unscheduled Case.

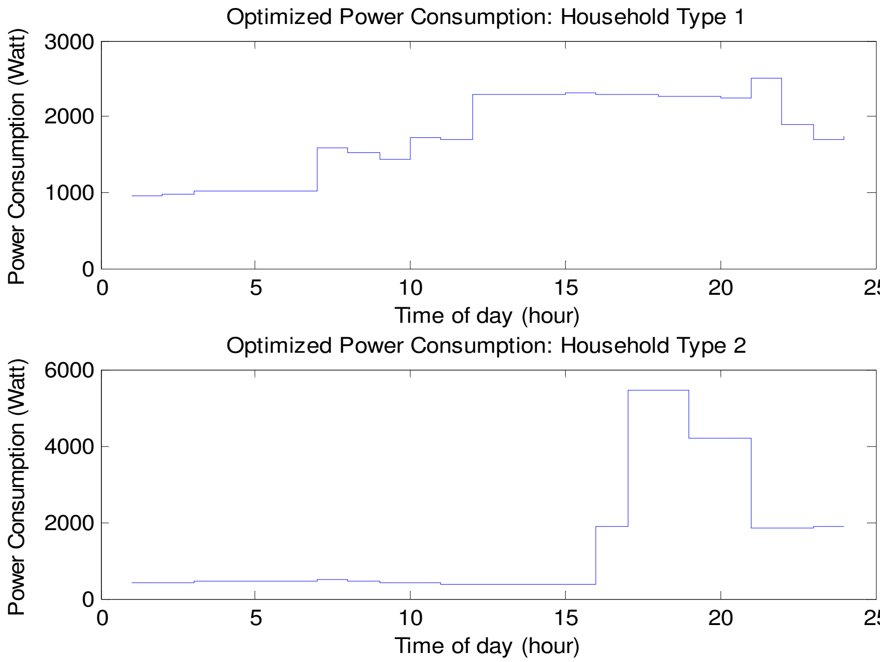


Figure 13. Load Profile of Scheduled Case. (# of Simulations: 1)

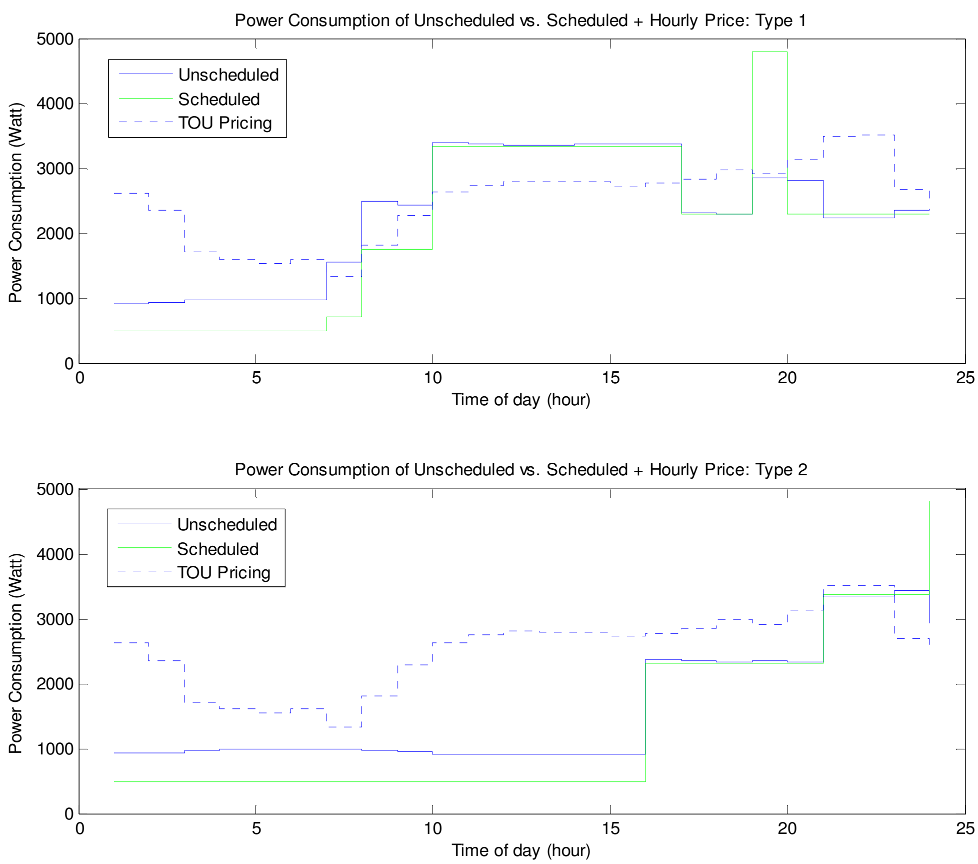


Figure 14. Comparison of Unscheduled and Scheduled Load Profiles with Price Data. (# of Simulations: 1)

From the results above, it can be inferred that the optimization algorithm generates power consumption vector that is lower than of the unscheduled scenario.

Results from 50 simulations are as follows.

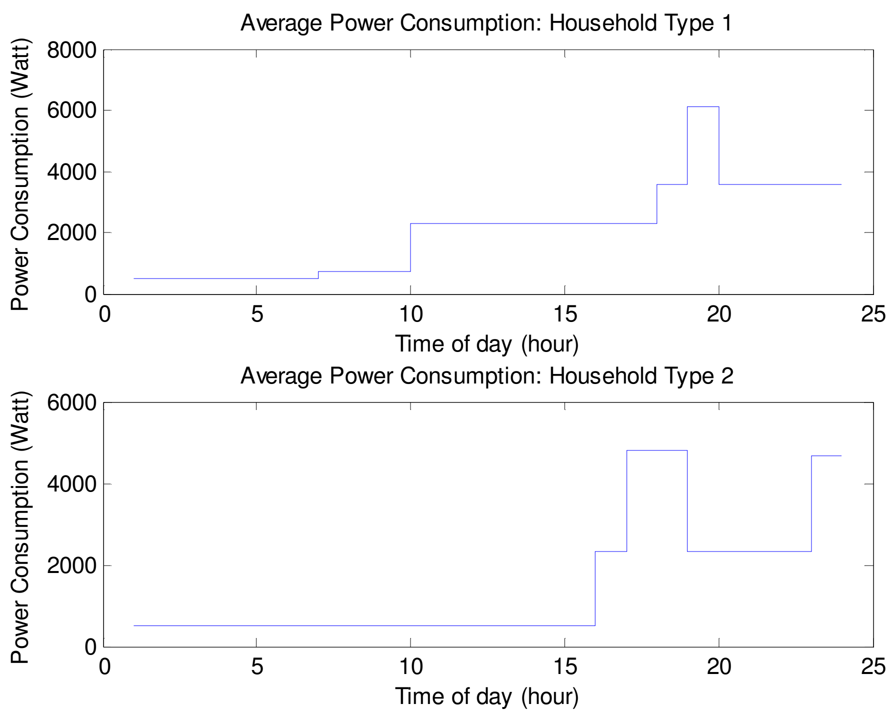


Figure 15: 24-Hour Load Profile without Scheduling

The total power consumption for the average of first and the second type of households is 45065 Watt and 36378 Watt, respectively.

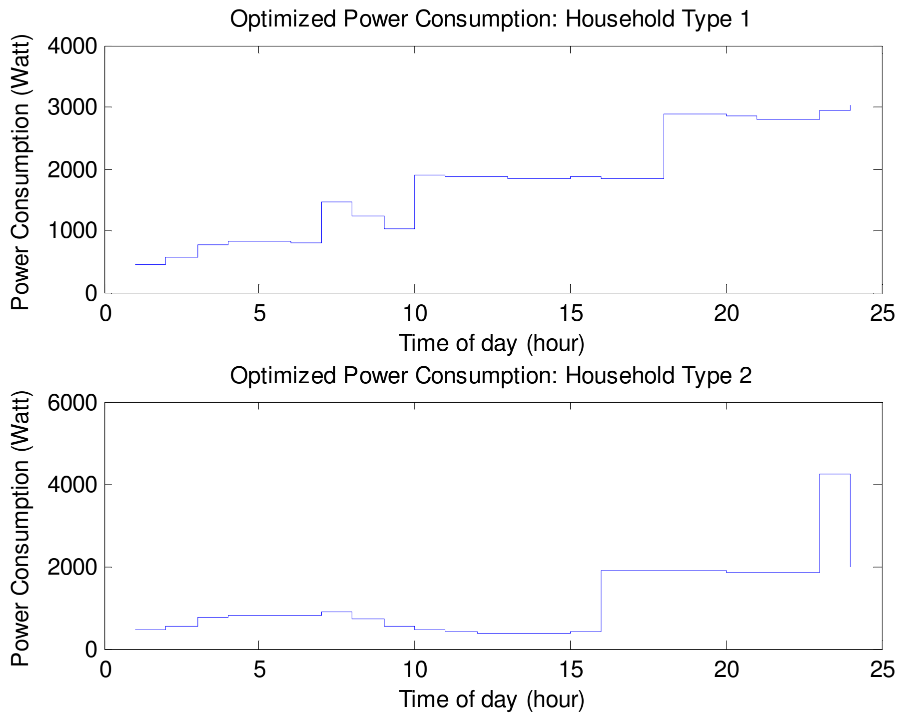


Figure 16: 24-Hour Load Profile with Scheduling

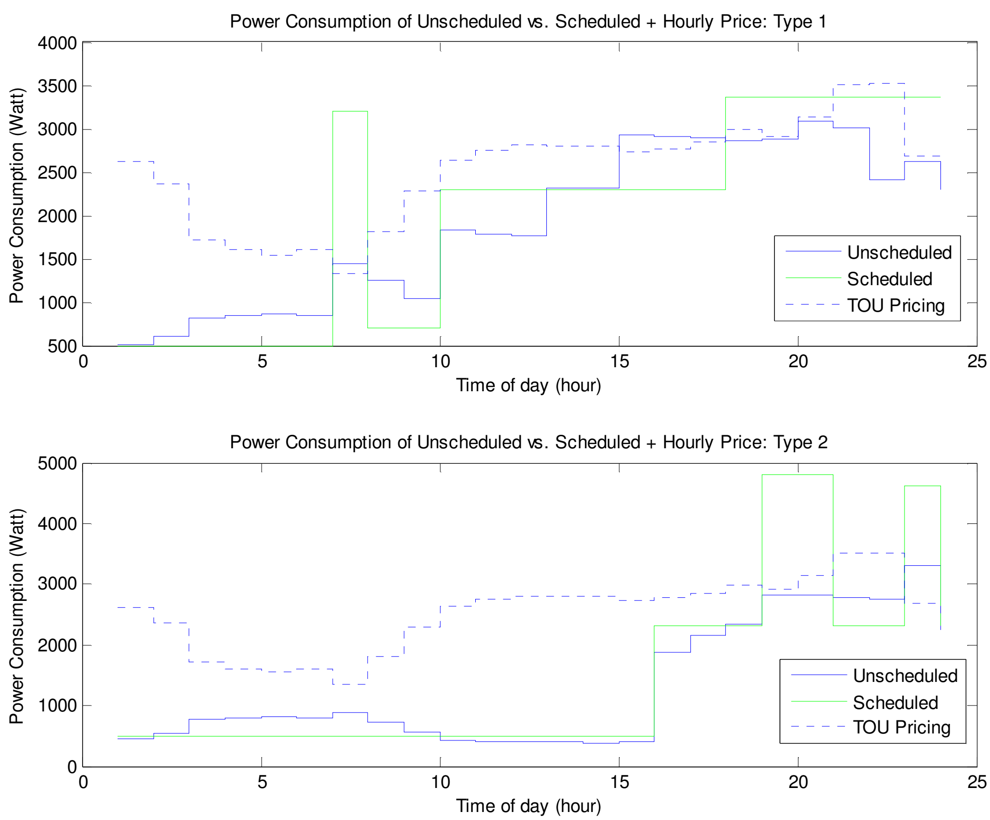


Figure 17: Comparison of Power Consumptin Vector for Unscheduled and Scheduled Cases

Household Type	Unscheduled (W)	Scheduled (W)
Type 1	45065	35857
Type 2	36378	21838
Average	40722	28848

Table 2: Comparison of Total Power Consumption throughout a day

Household Type	Unscheduled ($)	Scheduled ($)	Saving Rates (%)
Type 1	0.8348	0.7739	7.2952
Type 2	0.6057	0.5376	11.2432
Total	1.4405	1.3115	18.5384

Table 3: Comparison of Electricity Price

From the results, it can be observed the optimization algorithm reduces the total power consumption for both types of households. The results also show that there are significant saving rates for the total electricity bill. However, the algorithm does not fulfill the second goal of this project; it does not necessarily lower maximum total power consumption values – it does not perform peak-shaving at all occasions. One way for utility companies to utilize this data is to develop an algorithm to find out when the peak times are, and send signals to turn off background loads for that time intervals while making sure the constraints for performance of each load are satisfied.

V. Conclusion

In this paper, the author studied optimal demand response based on minimization of the total cost for two different types of households. The author provided mathematical models for each common electrical load as well as utility functions for three different categories of loads. Based on them, an optimization algorithm was developed. The results from simulations of the algorithm indicate that there exist power consumption vectors that can minimize the cost as well as satisfy home occupants' needs. Having known the demand response data, utility companies can develop programs to use the information to maximize their benefits; for example, they can incentivize for customers to join programs that will allow utility companies to turn off background loads such as air conditioners during peak usage times.

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Appendices

Appendix 1. m files for simulations of system model in [7]

Appendix 1a. objective.m

```
%Objective fuction:
%Set of appliances with elastic energy consumption without storage
function f = objective(x)

%Electricity price for each hour.
%Data extracted from the Central NY LMBP ($/MWHr) for 5/4/2013 Source:
NYISO
LBMP = [33.11, 31.79, 28.60, 28.01, 27.73, 28.03, 26.69, 29.09, 31.43,
33.20, 33.74, ...
    34.05, 34, 33.99, 33.64, 33.87, 34.25, 34.94, 34.59, 35.69, 37.56,
37.60, 33.41, 32.59];
price = LBMP.*0.000001.*0.5;
f = sum(x.*price);
```

Appendix 1b. constraint_class1.m

```
% Constraint function for class 1
function [c,ceq] = constraint_class1 (x,B_in,S_in,F_in,L_in)
c=B_in*L_in-sum(log(x(S_in:F_in)+1));
ceq = [];
```

Appendix 1c. constraint_class1.m

```
% Constraint function for class 2
function [c,ceq] = constraint_class2 (x,S_in,F_in,B_in)
c=B_in-sum(x(S_in:F_in));
ceq = [];
```

Appendix 1d. unscheduled.m

```
% Create 24-hour load profile without scheduling.
% Randomly generate parameters: starting time (S_a), finishing
time(F_a),
% maximum power consumption (x_a_max), and threshold (C_a).
% Power consumption data from each appliance for each sub-interval
% is calculated and stored into pw_matrix, and the total power
consumption
% for each sub-interval is stored into pw_consumption.

%-----Variables-----%
S_a = zeros(1,40); %Starting time
F_a = zeros(1,40); %Finishing time
```

```
L_a = zeros(1,40); %Length of time of operation
x_a_max = randi([0 1500],1,40); %Maximum power
B_a = zeros(1,40); %Performance threshold
pw_matrix = zeros(40,24); %Power consumption for each appliance for each
time interval
pw_consumption = zeros(1,24); %Total power for each time interval
%--------------------%

% For Class 1, background loads (appliance 1-20)
for m=1:20
S_a(m) = randi([1 24],1,1);
F_a(m) = randi([S_a(m) 24],1,1);
L_a(m) = F_a(m) - S_a(m) + 1;
%C_a(m) = L_a(m) * log(x_a_max(m)+1);
B_a(m) = randi([0 floor(log(x_a_max(m)+1))],1,1);
pw_matrix(m,S_a(m):F_a(m)) = x_a_max(m);
end

% For Class 2, interactive loads (appliance 21-40)
for m=21:40
S_a(m) = randi([1 24],1,1);
F_a(m) = randi([S_a(m) 24],1,1);
L_a(m) = F_a(m) - S_a(m) + 1;
%C_a(m) = L_a(m) * x_a_max(m);
B_a(m) = randi([0 floor(L_a(m) * x_a_max(m))],1,1);
pw_matrix(m,S_a(m):F_a(m)) = B_a(m);
end

for ii=1:24
pw_consumption(ii) = sum(pw_matrix(:,ii));
end
```

Appendix 1e. unscheduled_100.m

```
% Simulate the unscheduled load profile 100 times.
% Store all the results into vector y.
% Find the average of total power consumption for each time interval,
% store into vector pw_avg

y = zeros(100,24);
pw_avg = zeros(1,24);

for k=1:100
unscheduled
y(k,:) = pw_consumption;
end

for ii=1:24
pw_avg(ii)=sum(y(:,ii))/100;
end
```

Appendix 1f. scheduled.m

```
% Generate optimized schedule vector for each appliance.
% The same randomized parameters for unscheduled scenario are used.
% It is assumed that there are fourty appliances in total.
% Store the optimization results into vector optimized_pw.


unscheduled

x0=zeros(1,24);
lb=zeros(1,24);
opt_pw_matrix = zeros(40,24);
opt_pw = zeros(1,24);
opt_cost = zeros(1,24);
options=optimset('Algorithm','interior-point', 'Display', 'off');

%Find optimized power consumption schedule vector for each appliance
%Background loads (appliance 1-20)
for app_num=1:20
    [opt_pw_matrix(app_num,:),opt_cost(app_num)]=...
        fmincon...
        (@objective,x0,[],[],[],[],lb,[],...
        @(x)constraint_class1...

(x,B_a(app_num),S_a(app_num),F_a(app_num),L_a(app_num)),options);
end

%Interactive loads (appliance 21-40)
for app_num=21:40
[opt_pw_matrix(app_num,:),opt_cost(app_num)]=...
    fmincon(@objective,x0,[],[],[],[],lb,[],...

@(x)constraint_class2(x,S_a(app_num),F_a(app_num),B_a(app_num)),options)
;
end

for kk=1:24
opt_pw(kk)=sum(opt_pw_matrix(:,kk));
end

%
```

Appendix 2. m files for simulations of system model proposed by the author

Appendix 2a. main

```
%main.m

%Simulates optimization algorithm Jang-Won Lee and Du-Han Lee propose.
%Then, simulates the algorithm that the author proposes.

%First, unscheduled case is run 100 times, and the program asks the user
%whether or not to show 1) the average power consumption graph,
%2) the price graph, and 3) the electricity cost graph.

%Then, scheduled case with optimization is simulated.
%Prompts to user to decide whether or not to show
%1) the optimized power consumption graph and 2) the optimized cost
graph.

%Finally, shows the final result, which contains both
%power consumption graphs and electricity price for each time interval.

hold off
%*********************** Unscheduled Case ***********************%
disp('Run the unscheduled scenario 100 times and find the average power
consumption vector');
%unscheduled_100

answer=input('Show the average power consumption graph? (Y/N)','s');
if strcmp(answer,'Y')
   stairs(pw_avg);
   title('Average Power Consumption');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

% Calculate cost for each time interval
LBMP = [33.11, 31.79, 28.60, 28.01, 27.73, 28.03, 26.69, 29.09, 31.43,
33.20, 33.74, ...
    34.05, 34, 33.99, 33.64, 33.87, 34.25, 34.94, 34.59, 35.69, 37.56,
37.60, 33.41, 32.59];
price = LBMP.*0.000001.*0.5;

answer=input('Show the price graph? (Y/N)','s');
if strcmp(answer,'Y')
   stairs(price);
   title('Price of Electricity - Centural New York');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

answer=input('Show the electricity cost graph? (Y/N)','s');
if strcmp(answer,'Y')
   stairs(price.*pw_avg);
   title('Electricity Price');
   xlabel('Time of day (hour)');
```

```
   ylabel('Power Consumption (Watt)');
end


pause(2);


%*********************** Scheduled Case **********************%
disp('Run the scheduled scenario. (Takes a couple minutes...)');
%scheduled

answer=input('Show the optimized power consumption graph? (Y/N)','s');
if strcmp(answer,'Y')
   stairs(opt_pw);
   title('Optimized Power Consumption');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

answer=input('Show the optimized electricity cost graph? (Y/N)','s');
if strcmp(answer,'Y')
   stairs(price.*opt_pw);
   title('Electricity Price');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end


%*********************** Comparison **********************%
disp('Type Y to show the comparison of power consumption');
answer = input('between unscheduled and scheduled case: ','s');
if strcmp(answer,'Y')
   stairs(opt_pw,'blue');
   hold on
   stairs(pw_avg,'green');
   stairs(price*1.0e09*4-5.0e04,':');
   title('Power Consumption of Unscheduled vs. Scheduled + Hourly
Price');
   legend('Unscheduled','Scheduled','TOU Pricing');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end
hold off
```

```
%::::::::::::::::::::::::::::::::::%
%::::::::::New Algorithm::::::::::%
%::::::::::::::::::::::::::::::::::%

%*********************** Unscheduled Case ***********************%
disp(' ');
disp('Test the algorithm created by the author.');
disp('Run the unscheduled scenario 100 times and find the average power
consumption vector');
unscheduled_new

answer=input('Show the average power consumption graph? (Y/N)','s');
if strcmp(answer,'Y')
   subplot(2,1,1), stairs(pw_consumption_1);
   title('Average Power Consumption: Household Type 1');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
   subplot(2,1,2), stairs(pw_consumption_2);
   title('Average Power Consumption: Household Type 2');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

% Calculate cost for each time interval
LBMP = [33.11, 31.79, 28.60, 28.01, 27.73, 28.03, 26.69, 29.09, 31.43,
33.20, 33.74, ...
    34.05, 34, 33.99, 33.64, 33.87, 34.25, 34.94, 34.59, 35.69, 37.56,
37.60, 33.41, 32.59];
price = LBMP.*0.000001.*0.5;


answer=input('Show the electricity cost graph? (Y/N)','s');
if strcmp(answer,'Y')
   subplot(2,1,1), stairs(price.*pw_consumption_1);
   title('Electricity Cost: Household Type 1');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
   subplot(2,1,2), stairs(price.*pw_consumption_2);
   title('Electricity Price: Household Type 2');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end


pause(2);


%*********************** Scheduled Case ***********************%
disp('Run the scheduled scenario. (Takes a couple minutes...)');
scheduled_100_new

answer=input('Show the optimized power consumption graph? (Y/N)','s');
if strcmp(answer,'Y')
    subplot(2,1,1), stairs(opt_pw1);
   title('Optimized Power Consumption: Household Type 1');
```

```
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
    subplot(2,1,2), stairs(opt_pw2);
   title('Optimized Power Consumption: Household Type 2');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

answer=input('Show the optimized electricity cost graph? (Y/N)','s');
if strcmp(answer,'Y')
   subplot(2,1,1), stairs(price.*opt_pw1);
   title('Electricity Cost: Household Type 1');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
   subplot(2,1,2), stairs(price.*opt_pw2);
   title('Electricity Cost: Household Type 2');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end

%*********************** Comparison ***********************%
disp('Type Y to show the comparison of power consumption');
answer = input('between unscheduled and scheduled case: ','s');
if strcmp(answer,'Y')
   subplot(2,1,1), stairs(opt_pw_avg1,'blue');
   hold on
   stairs(pw_consumption_1,'green');
   stairs(4.*price*1.0e08-4000,':');
   title('Power Consumption of Unscheduled vs. Scheduled + Hourly Price:
Type 1');
   legend('Unscheduled','Scheduled','TOU Pricing');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');

   subplot(2,1,2), stairs(opt_pw_avg2,'blue');
   hold on
   stairs(pw_consumption_2,'green');
   stairs(4.*price*1.0e08-4000,':');
   title('Power Consumption of Unscheduled vs. Scheduled + Hourly Price:
Type 2');
   legend('Unscheduled','Scheduled','TOU Pricing');
   xlabel('Time of day (hour)');
   ylabel('Power Consumption (Watt)');
end
```

Appendix 2b. unscheduled_new

```
%%%This m-file simulates unscheduled scenario with new settings set by
%%%the author.

% Power consumption data from each appliance for each sub-interval
% is calculated and stored into pw_matrix, and the total power
consumption
% for each sub-interval is stored into pw_consumption.

% Two types of households (50 each) are considered:
% 1) Occupants stay at home the entire day
% 2) Occupants leave the house at 9 a.m. and return at 5 p.m.

% Appliances
% 1: Air-Conditioner 2: Refrigerator 3: Light w/ Controllable Brightness
% 4: Washer 5: Light w/o Controllable Brightness 6: Entertainment
Station

%-----Variables-----%
%Type1
pw_matrix_1 = zeros(6,24); %Power consumption for each appliance for
each time interval
pw_consumption_1 = zeros(1,24); %Total power for each time interval
x_a_min_1 = zeros(6,24); %Minimum power for each appliance
x_a_max_1 = zeros(6,24); %Maximum power for each appliance
S_a_1 = zeros(1,6); %Starting time for each appliance
F_a_1 = zeros(1,6); %Finishing time for each appliance
L_a_1 = zeros(1,6); %Length of time of operation for each appliance
B_a_1 = zeros(1,6); %Performance threshold for each appliance

%Type2
pw_matrix_2 = zeros(6,24); %Power consumption for each appliance for
each time interval
pw_consumption_2 = zeros(1,24); %Minimum power for each appliance
x_a_min_2 = zeros(6,24); %Minimum power for each appliance
x_a_max_2 = zeros(6,24); %Maximum power
S_a_2 = zeros(1,6); %Starting time for each appliance
F_a_2 = zeros(1,6); %Finishing time for each appliance
L_a_2 = zeros(1,6); %Length of time of operation for each appliance
B_a_2 = zeros(1,6); %Performance threshold for each appliance

pw_consumption=zeros(1,24); %Total power consumption for each time
interval
%-------------------%



%%%Air-Conditioner%%% *Background*
%Assumption: Home occupants wake up at 7 in the morning, go to sleep at
12 -
%the occupants need not the AC on while they are sleeping.
%Temperature variation pattern throughout the day resembles
%an upside-down vertical parabola; it gradually increases until it hits
the maximum
%value and gradually decreases. Also,
appnum=1;
```

```
x_a_max_1(appnum,:)=1600;
x_a_min_1(appnum,:)=1000;
x_a_max_2(appnum,:)=1600;
x_a_min_2(appnum,:)=1000;
temperature = [78 74 72 69 68 67 70 73 78 83 87 89 92 96 95 94 95 95 94
91 86 86 84 78];
%Type 1 households
for time=7:24
    if temperature(time) > 78
        S_a_1(appnum) = time;
        break;
    end
end
for time=S_a_1(appnum):24
    if temperature(time) <= 78
        F_a_1(appnum) = time;
        break;
    end
end
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = floor(log(x_a_max_1(appnum)+1));
pw_matrix_1(appnum,S_a_1(appnum):F_a_1(appnum)) = x_a_max_1(appnum);

%Type 2 households
for time=16:24
    if temperature(time)>78
        S_a_2(appnum) = time;
        break;
    end
end

for time=S_a_2(appnum):24
    if temperature(time) <= 78
        F_a_2(appnum) = time;
        break;
    end
end
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = floor(log(x_a_max_2(appnum)+1));
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = x_a_max_2(appnum);
%%%%%%%%%%%%%%%%%%



%%%Refrigerator%%% *Background*
%Assumtion: Home occupants wake up at 7 in the morning, go to sleep at
12.
%The do not open the fridge while they are sleeping.
appnum=2;
x_a_max_1(appnum,:)=500;
x_a_min_1(appnum,:)=150;
x_a_max_2(appnum,:)=500;
x_a_min_2(appnum,:)=150;
S_a_1(appnum)=1;
S_a_2(appnum)=1;
F_a_1(appnum)=24;
```

```
F_a_2(appnum)=24;
%Type 1 households
for time=7:24
    opennum=abs(floor(3 + 1.333.*randn(1,1)));
    x_a_min_1(appnum,time) = x_a_min_1(appnum,time)+opennum*20;
end
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = floor(log(x_a_max_1(appnum)+1));
pw_matrix_1(appnum,S_a_1(appnum):F_a_1(appnum)) = x_a_max_1(appnum);

%Type 2 households
for time=17:24
    opennum=abs(floor(3 + 1.333.*randn(1,1)));
    x_a_min_2(appnum,time) = x_a_min_2(appnum,time)+opennum*20;
end
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = floor(log(x_a_max_2(appnum)+1));
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = x_a_max_2(appnum);
%%%%%%%%%%%%%%%%%%


%%%Light w/ Controllable Brightness%%% *Background*
appnum=3;
x_a_max_1(appnum,:)=800;
x_a_min_1(appnum,:)=200;
x_a_max_2(appnum,:)=800;
x_a_min_2(appnum,:)=200;
%Type 1 households
S_a_1(appnum) = 7;
F_a_1(appnum) = 24;
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = floor(log(x_a_max_1(appnum)+1));
pw_matrix_1(appnum,S_a_1(appnum):F_a_1(appnum)) = B_a_1(appnum);

%Type 2 households
S_a_2(appnum) = 16;
F_a_2(appnum) = 24;
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = floor(log(x_a_max_2(appnum)+1));
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = B_a_2(appnum);
%%%%%%%%%%%%%%%%%%


%%%Washer%%% *Interactive - Schedulable*
%Assumption: the appliance has functions that can delay operation.
%It takes less than an hour to finish one cycle.
appnum=4;
x_a_max_1(appnum,:)=2500;
x_a_min_1(appnum,:)=1400;
x_a_max_2(appnum,:)=2500;
x_a_min_2(appnum,:)=1400;
%Type 1 households
S_a_1(appnum) = randi([7 24],1,1);
if S_a_1(appnum)==24
    F_a_1(appnum) = 24;
else
```

```
    F_a_1(appnum) = S_a_1(appnum)+1;
end
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = x_a_max_1(appnum);
pw_matrix_1(appnum,S_a_1(appnum)) = x_a_max_1(appnum);

%Type 2 households
S_a_2(appnum) = randi([16 24],1,1);
if S_a_2(appnum)==24
    F_a_2(appnum) = 24;
else
    F_a_2(appnum) = S_a_2(appnum)+1;
end
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = x_a_max_2(appnum);
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = x_a_max_2(appnum);
%%%%%%%%%%%%%%%%%%



%%%Light w/o Controllable Brightness%%% *Interactive*
%Assumption: This appliance cannot be scheduled.
appnum=5;
x_a_max_1(appnum,:)=200;
x_a_min_1(appnum,:)=100;
x_a_max_2(appnum,:)=200;
x_a_min_2(appnum,:)=100;
%Type 1 households
S_a_1(appnum) = 7;
F_a_1(appnum) = 24;
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = x_a_max_1(appnum);
pw_matrix_1(appnum,S_a_1(appnum):F_a_1(appnum)) = x_a_max_1(appnum);

%Type 2 households
S_a_2(appnum) = 16;
F_a_2(appnum) = 24;
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = floor(log(x_a_max_2(appnum)+1));
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = x_a_max_2(appnum);
%%%%%%%%%%%%%%%%%%


%%%Entertainment Station%%% *Interactive*
%Assumption: This appliance cannot be scheduled.
appnum=6;
x_a_max_1(appnum,:)=randi(3500,[1,1]);
x_a_min_1(appnum,:)=0;
x_a_max_2(appnum,:)=randi(3500,[1,1]);
x_a_min_2(appnum,:)=0;
%Type 1 households
S_a_1(appnum) = randi([7,24],1,1);
F_a_1(appnum) = randi([S_a_1(appnum),24],1,1);
L_a_1(appnum) = F_a_1(appnum) - S_a_1(appnum) + 1;
B_a_1(appnum) = floor(x_a_max_1(appnum));
```

```
pw_matrix_1(appnum,S_a_1(appnum):F_a_1(appnum)) = x_a_max_1(appnum);


%Type 2 households
S_a_2(appnum) = randi([16,24],1,1);
F_a_2(appnum) = randi([S_a_2(appnum),24],1,1);
L_a_2(appnum) = F_a_2(appnum) - S_a_2(appnum) + 1;
B_a_2(appnum) = floor(log(x_a_max_2(appnum)+1));
pw_matrix_2(appnum,S_a_2(appnum):F_a_2(appnum)) = x_a_max_2(appnum);
%%%%%%%%%%%%%%%%%%

for ii=1:24
pw_consumption_1(ii) = sum(pw_matrix_1(:,ii));
end

for ii=1:24
pw_consumption_2(ii) = sum(pw_matrix_2(:,ii));
end

for ii=1:24
pw_consumption(ii) = sum(pw_matrix_1(:,ii)) + sum(pw_matrix_2(:,ii));
end
```

Appendix 2c. scheduled_new.m

```
% Generate optimized schedule vector for each appliance.
% The same randomized parameters for unscheduled scenario are used.
% It is assumed that there are fourty appliances in total.
% Store the optimization results into vector optimized_pw.


unscheduled_new

x0=zeros(1,24);
lb=zeros(1,24);
opt_pw_matrix1 = zeros(6,24);
opt_pw_matrix2 = zeros(6,24);
opt_pw1 = zeros(1,24);
opt_pw2 = zeros(1,24);
opt_cost = zeros(1,24);
options=optimset('Algorithm','interior-point', 'Display', 'off');

%Find optimized power consumption schedule vector for each appliance
%Background Loads
%AC, Refrigerator, and Light w/ Controllable Brightness
for app_num=1:3;
%Type1
    [opt_pw_matrix1(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_1(appnum,:),x_a_max_1(appnum,:),...
```

```
        @(x)constraint_class1...

(x,B_a_1(app_num),S_a_1(app_num),F_a_1(app_num),L_a_1(app_num)),options)
;

%Type2
    [opt_pw_matrix2(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_2(appnum,:),x_a_max_2(appnum,:),...
        @(x)constraint_class1...

(x,B_a_2(app_num),S_a_2(app_num),F_a_2(app_num),L_a_2(app_num)),options)
;

end

%Schedulable Interactive Loads
%Washer
%Assumption: This appliance can be moved to any time of day; there
exists a
%funtion that allows delay of operation to time intervals that have
cheaper
%cost.
app_num=4;
%Type1
    [opt_pw_matrix1(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_1(appnum,:),x_a_max_1(appnum,:),...
        @(x)constraint_class2...
        (x,1,24,B_a_1(app_num)),options);

%Type2
    [opt_pw_matrix2(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_2(appnum,:),x_a_max_2(appnum,:),...
        @(x)constraint_class2...
        (x,1,24,B_a_2(app_num)),options);

%Light without Controllable Brightness
app_num=5;
%Type1
    [opt_pw_matrix1(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_1(appnum,:),x_a_max_1(appnum,:),...
        @(x)constraint_class2...
        (x,S_a_1(app_num),F_a_1(app_num),B_a_1(app_num)),options);

%Type2
    [opt_pw_matrix2(app_num,:),opt_cost(app_num)]=...
        fmincon...

(@objective,x0,[],[],[],[],x_a_min_2(appnum,:),x_a_max_2(appnum,:),...
```

```
        @(x)constraint_class2...
        (x,S_a_2(app_num),F_a_2(app_num),B_a_2(app_num)),options);


%Unschedulable Interactive Loads
%Entertainment Station
%This cannot be scheduled.
app_num=6;
opt_pw_matrix1(app_num,:) = pw_matrix_1(app_num,:); %Type1
opt_pw_matrix2(app_num,:) = pw_matrix_2(app_num,:); %Type2

for kk=1:24
opt_pw1(kk)=sum(opt_pw_matrix1(:,kk));
end

for kk=1:24
opt_pw2(kk)=sum(opt_pw_matrix2(:,kk));
end
%
```

Appendix 2d. scheduled_100_new.m

```
% Simulate the scheduled load profile 100 times.
% Store all the results into vector y.
% Find the average of total power consumption for each time interval,
% store into vector pw_avg

y = zeros(100,24);
opt_pw_avg1 = zeros(1,24);
opt_pw_avg2 = zeros(1,24);

for k=1:5
scheduled_new
y(k,:) = opt_pw1;
end

for k=6:10
scheduled_new
y(k,:) = opt_pw2;
end

for ii=1:24
opt_pw_avg1(ii)=sum(y(1:5,ii))/5;
opt_pw_avg2(ii)=sum(y(6:10,ii))/5;
end
```

Capstone Summary

Smart Home System denotes a control system for electrical appliances in households. The system can be designed to enable two-way communication between the electricity provider and its customers, to achieve various goals: mainly, to reduce energy consumption and to flatten electricity demand.

Electric utilities, the government and research institutions are continuously making investments in developing Smart Home technologies. Incentives for developing these technologies are limited amount of coal and oil, green house effects, expenses of renewable resources, and investment costs on the utility side. Typical energy usage patterns in households display peaks and troughs throughout a day; usually, peaks occur during meal times when home occupants are using kitchen appliances and also in the evening when most people are at home, using electrical appliances at their convenience. As we become more dependent on electrical appliances and the maximum amount of electricity demand during peak times increases, there are more investments the utility companies have to make in order to accommodate the demand. They would need to build more transmission lines and substations, which are not cost-efficient – the demand would not meet the maximum capacity the entire time. Therefore, shifting a part of demand from peak hours to trough hours – demand flattening – benefits the utility companies.

Recent studies include evaluations of electricity usage patterns in households and development of electrical load management strategies. It has been proven difficult to design a control system that will reduce demand during peak hours, because turning off appliances requires active consumer involvement (source: SmartCap). The author of this project, "Energy-Efficient Smart Home System: Optimization of Electricity Demand in

Residential Buildings," proposes a strategy for utility companies to reduce power consumption during peak demand. Before introducing the strategy, it is assumed that the utility company employs a time-of-use (TOU) pricing model, which reflects the demand; the higher the demand, the more the company charges for electricity usage. By implementing the TOU model, the utilities are able to incentivize using less energy during peak demands.

The project proposes an optimization algorithm for minimizing the total electricity bill. The algorithm finds a power consumption vector for each appliance, which includes power consumption value for each hour. The goals of the algorithm are to lower the total energy consumption as well as find when peak hours are, in order for utility companies to use the information to shed the loads during those hours.

A system model for a household setting is presented and used to simulate a 24-hour power consumption profile. The system model consists of mathematical models for three different types of electrical appliances, which are called *background loads, schedulable interactive loads* and *unschedulable interactive loads*. *Background loads* are appliances that usually operate in the background and are transparent to the home occupants – the examples include air conditioners and refrigerators. As long as power consumption of these loads for each hour is above a certain threshold, it does not matter how much energy it consumes and when they turn on and off. These appliances can be used to significantly lower the total power consumption during peak hours, by controlling the magnitude and schedule of these loads. *Schedulable interactive loads* are appliances such as washers and dish washers. These appliances require interaction with the user, such as putting clothes or dishes into the machine. However, there have been companies, GE, LG and Samsung for example, that implement delay functions into these appliances so that the operation can be re-scheduled to low demand hours. Managing the power consumption and the time of operation of these appliances can also help lower the overall energy demand and flatten the demand. *Unschedulable interactive loads* indicate electrical appliances that are apparent to home occupants. Satisfaction of the users for appliances such as microwave, TV, and computer is highly dependent on whether or not they can use these appliances at their convenience, freely; you want to watch TV when you want to, and check e-mails when you want to. In this project, magnitude and time of operation for these appliances are not controlled, yet it is assumed that they can be monitored so the utility companies can use the information to flatten the demand. This project presents mathematical models for all of the appliances considered. The author incorporates distinct characteristics and operation patterns of each appliance and creates a load profile for each hour by randomizing parameters for each appliance. These parameters include starting time, ending time, and minimum and maximum power consumption threshold.

To perform optimization, a MATLAB function 'fmincon' is utilized. Optimization requires objective function and constraint functions, and the software finds a vector that satisfies the constraints and minimizes the value defined in objective function. Constraint functions indicate that the performance of each appliance is higher than its threshold. Performance is determined by using a utility function, which is assumed to be increasing and strictly concave. The performance value represents satisfaction of home occupants – as long as the performance exceeds a certain threshold, the home occupants does not experience any discomfort.

To find out whether or not the optimization algorithm finds desired outcome, the original system model from an article by Du-Han Lee and Jang-Won Lee is simulated. Then, the system model that this project proposes is simulated. In an attempt to generate more realistic outcome, two types of households are defined: for type one, home occupants are assumed to stay at home the whole day; for second type, home occupants leave home for work at 9am and get back at 5pm, and the home is empty between those two hours. The algorithm is simulated once for the system model, and then fifty times for each type of household.

The results from hundred simulations in total demonstrate that there are significant savings of approximately 18.5% in the electricity bill for the customers. The decrease in total power consumption and electricity cost is beneficial for the customers as well as the environment. However, the peaks of high demand are higher with the optimization, partially due to unschedulable interactive loads, which implies more investment costs for the utility companies. The author suggests that utility companies can employ the information on electricity demand to perform peak-shaving for their customers, by sending signals to the system to turn off background loads. There exist programs that utilities invite customers to join, which enable utilities' access to control certain appliances. Incorporation of these programs to the algorithm would maximize economical as well as environmental benefits.