AMS-559 Smart Energy in the Information Age Project-2

Submitted By: Anuroop Katiyar 112609023

Electricity Provisioning Based on Demand Prediction

Overview:

The goal of this homework is to test the performance of different electricity provisioning algorithms based on the demand predictions we obtained in Homework 1. The below Objective function is used to measure the performance of the different algorithms:

$$\sum_{t=1}^{T} p(t)x(t) + a * \max\{0, y(t) - x(t)\} + b|x(t) - x(t-1)|$$

The values of a=b=\$4/kwh and p=\$0.40/kwh, unless stated otherwise.

Tasks:

- 1. Solve the offline optimization problem, e.g., using tools CVX in Matlab or Python.
- 2. Try online gradient descent (with different step size), receding horizon control (with different prediction window size), commitment horizon control (with different commitment levels). For the latter two algorithms, use predictions from at least two prediction algorithms for the default value of a and b.
- 3. Compare the costs of these algorithms to those of the offline static and dynamic solutions.
- 4. For the best combination of control algorithm and prediction algorithm, vary a and b to see the impacts.
- 5. Try at least two algorithm selection (one deterministic, one randomized) to see if their performance.

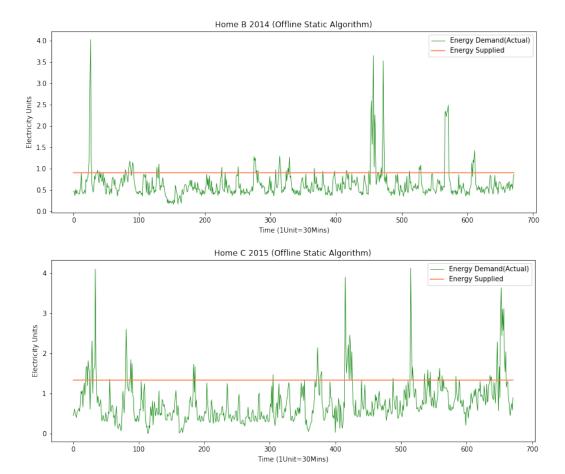
1. Offline Optimization Solution:

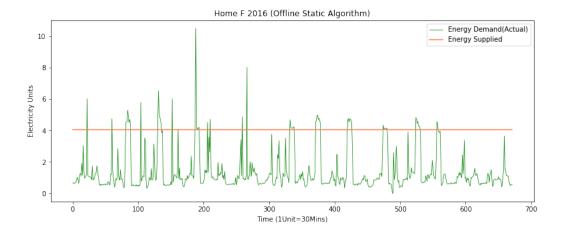
(a) Offline Static Optimization: In this optimization, we do not take the switching cost into account, so our function reduces to below:

$$\sum_{t=1}^{T} p(t)x(t) + a * \max\{0, y(t) - x(t)\}\$$

Using the above expression, I have calculated the optimal value for energy supply and plotted the graph for all 3 houses.

House	Optimal Value
Home B – 2014	192.50065
Home C – 2015	257.28039
Home F – 2016	638.46939



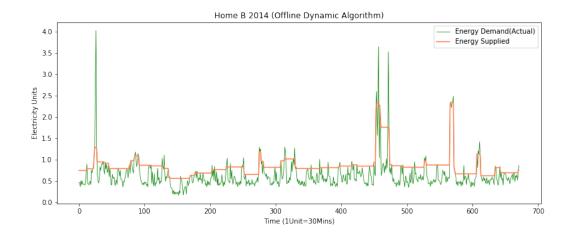


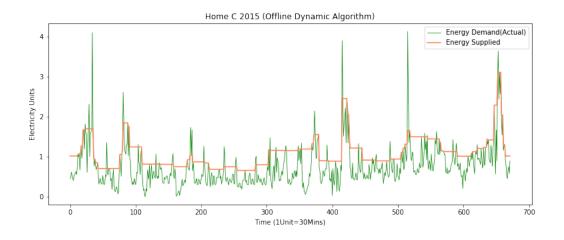
(b) Offline Dynamic Optimization: In this optimization, we consider both costs i.e. the penalty('a') and the switching cost('b'). So, our performance is measured using the below function:

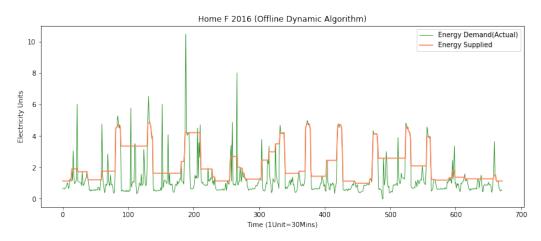
$$\sum_{t=1}^{T} p(t)x(t) + a * \max\{0, y(t) - x(t)\} + b|x(t) - x(t-1)|$$

Using the above expression, I have calculated the optimal value for energy supply and plotted the graph for all 3 houses.

House	Optimal Value
Home B – 2014	160.39251
Home C – 2015	209.88195
Home F – 2016	491.68934







2. Online Optimization Solution:

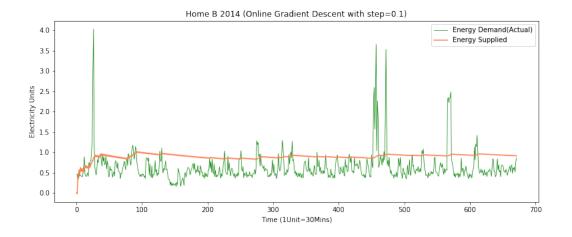
(a) Online Gradient Descent: In this algorithm, we calculate the value of x(t) iteratively using the previous value of x. The equation used is as below:

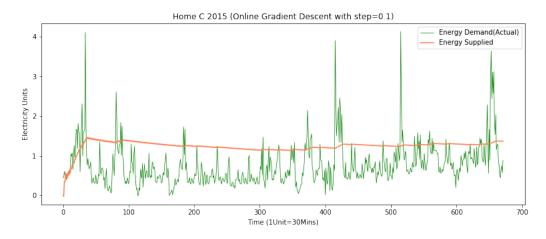
$$x(t+1) = x(t) - learningRate*(\partial f(x(t))/x(t)))$$

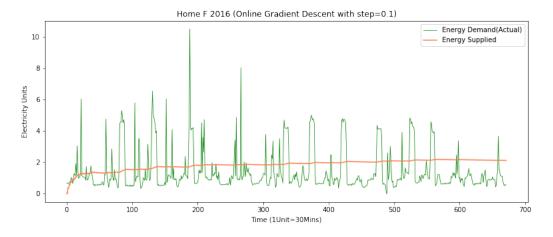
I tried multiple step sizes for this algorithm and observed the changes in optimal value returned by the function. The results are given in the table below:

House	Optimal	Optimal	Optimal	Optimal	Optimal
	Value	Value	Value	Value	Value
	(Step - 0.01)	(Step - 0.05)	(Step - 0.1)	(Step - 0.5)	(Step - 1.0)
Home B – 2014	178.81228	129.31317	129.97036	148.36560	173.69895
Home C – 2015	220.83781	171.22591	168.20425	188.48466	212.35817
Home F – 2016	440.10817	356.29337	343.59002	363.18620	389.32345

As observed in the table above, we have selected the step size 0.1 for our plots because it returns the best optimal values.



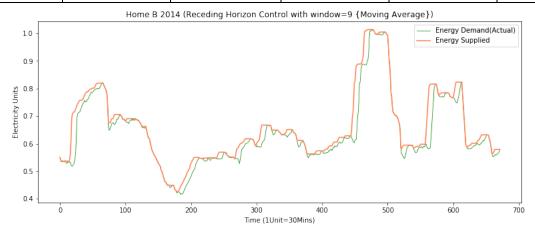


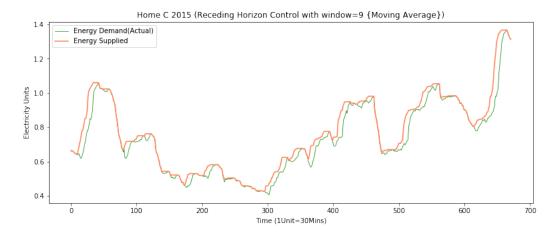


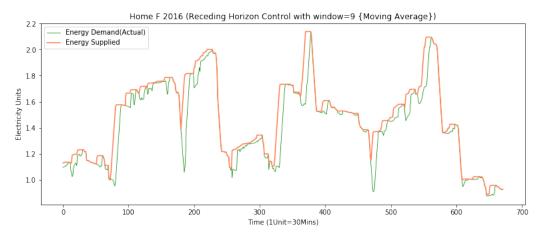
- **(b)** Receding Horizon Control: RHC algorithm is also popularly known as Model Predictive Control. I have first tried to implement RHC over different window sizes to minimize our objective function. For the demand values I have used prediction values from the below 2 prediction algorithms:
- i. Moving Average
- ii. Linear Regression

Results obtained for RHC over different window sizes using **Moving Average predictions** are as below:

House	Optimal	Optimal	Optimal	Optimal	Optimal
(Moving Average	Value	Value	Value	Value	Value
Prediction)	(Window=3)	(Window=5)	(Window=7)	(Window=9)	(Window=11)
Home B – 2014	232.80153	229.20210	226.96833	225.60229	225.15000
Home C – 2015	343.20469	336.73118	331.55018	327.04963	325.67004
Home F – 2016	813.04809	802.66587	795.21284	790.18615	788.76597

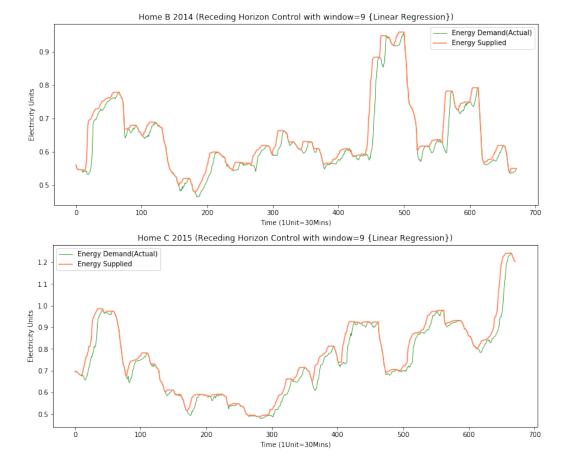


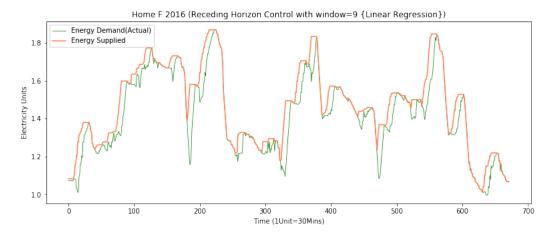




Results obtained for RHC over different window sizes using **Linear Regression predictions** are as below:

House	Optimal	Optimal	Optimal	Optimal	Optimal
(Linear Regr.	Value	Value	Value	Value	Value
Prediction)	(Window=3)	(Window=5)	(Window=7)	(Window=9)	(Window=11)
Home B – 2014	231.71473	228.51478	226.40423	225.07099	224.77527
Home C – 2015	339.14967	334.03477	330.03484	326.36931	325.01588
Home F – 2016	809.20079	801.83945	796.94377	793.81083	793.87038

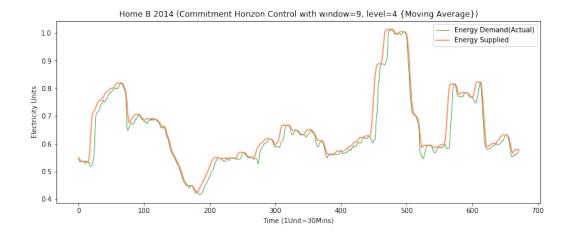


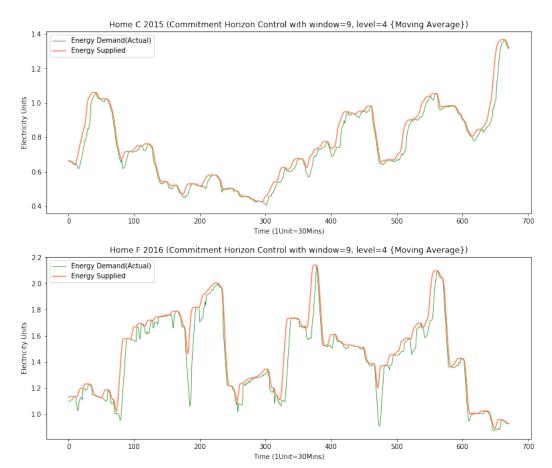


- (c) Commitment Horizon Control: I have first tried to implement CHC over different commitment levels to minimize our objective function. For the demand values I have used prediction values from the below 2 prediction algorithms:
- i. Moving Average
- ii. Linear Regression

Results obtained for CHC over different commitment levels using **Moving Average predictions** are as below:

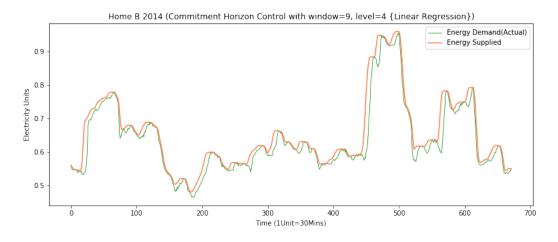
House	Optimal Value	Optimal Value	Optimal Value
(Moving Average	(Level=2)	(Level=4)	(Level=6)
Prediction)			
Home B – 2014	225.71445	226.05354	226.53093
Home C – 2015	327.81760	329.22728	330.59954
Home F – 2016	790.51481	791.50267	792.97432

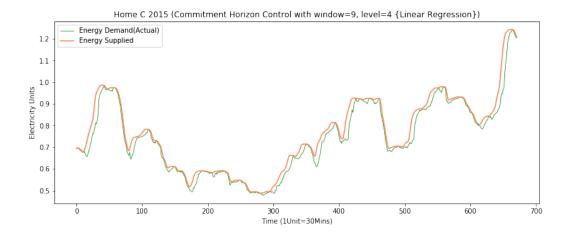


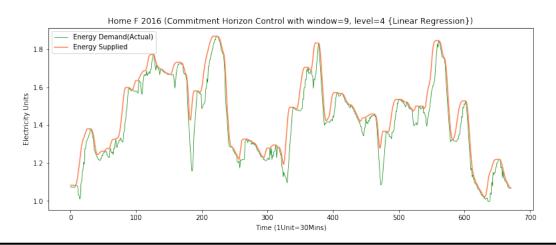


Results obtained for CHC over different commitment levels using **Linear Regression predictions** are as below:

House (Linear Regression Prediction)	Optimal Value (Level=2)	Optimal Value (Level=4)	Optimal Value (Level=6)
Home B – 2014	225.06903	225.30484	225.71480
Home C – 2015	327.00802	328.30393	329.58660
Home F – 2016	794.03747	794.41845	795.05612







3. Final Comparison Table:

The results of all the offline and online provisioning algorithms have been summarized in the table below:

Houses	Offline	Online	Online	RHC	RHC	CHC	CHC
	Static	Static	Gradient	(Moving	(Linear	(Moving	(Linear
			Descent	Average)	Regre.)	Average)	Regre.)
Home B	192.500651	160.392507	219.054541	225.602290	225.070990	226.053545	225.304840
(2014)							
Home C	257.280387	209.881952	287.626093	327.049632	326.369313	329.227275	328.303930
(2015)							
Home F	638.469395	491.689337	786.719014	790.186148	793.810832	791.502668	794.418449
(2016)							

4. Varying costs for best algorithm combination:

As can be seen from the above table, our best combination of control and prediction algorithm is RHC using Linear Regression predictions. We now tried various combinations of penalty('a') and switching('b') cost, the results of which are given below:

Houses	a=8 and b=2 (kW/hr)	a=6 and b=6 (kW/hr)	a=2 and b=8 (kW/hr)
Home B (2014)	354.60580	293.79093	164.45231
Home C (2015)	535.63878	436.28517	226.81379
Home F (2016)	1372.23405	1096.09801	520.82355

As we can see from the above table, the minimum optimal values are produced when we take a=\$2.0 kW/hr and b=\$8.0 kW/hr. This suggests that reducing the penalty reduces our objective function values considerably.

5. Algorithm Selection:

- (a) Deterministic Algorithm:
 - i. Assign equal weights to all 3 algorithms, $w_1=w_2=w_3=1$.
 - ii. For the given duration T=672, divide into equal smaller intervals.
- iii. For each interval obtain the objective function for all 3 online algorithms OGD, CHC and RHC and compare with Offline solution.
- iv. Choose the algorithm with the maximum weight.
- v. If chosen algorithm is correct keep the same weight, else reduce the weight by 0.1 to penalize.

Results:

Minimum Optimal Values at different intervals

---- homeB --------- homeC --------- homeF ----Total Intervals: 84.0 Total Intervals: 84.0 Total Intervals: 84.0 OGD Used: 8 times OGD Used: 10 times OGD Used: 12 times RHC Used: 9 times RHC Used: 11 times RHC Used: 12 times CHC Used: 63 times CHC Used: 67 times CHC Used: 60 times Optimal value: 270.23746 Optimal value: 420.10343 Optimal value: 951.22283

(b) Randomized Algorithm:

- i. Assign random weights to all 3 online algorithms.
- ii. For the given duration T=672, divide into equal smaller intervals.
- iii. Choose the algorithm which has the highest weighted probability.
- iv. Compute the objective function for the chosen algorithm.
- v. Continue the same steps for all the intervals.

Results:

Minimum Optimal Values at different intervals

homeB	homeC	homeF
Total Intervals: 56.0	Total Intervals: 56.0	Total Intervals: 56.0
OGD Used: 20 times	OGD Used: 15 times	OGD Used: 15 times
RHC Used: 17 times	RHC Used: 16 times	RHC Used: 21 times
CHC Used: 19 times	CHC Used: 25 times	CHC Used: 20 times

Conclusion:

As we can see that neither deterministic, nor random algorithm selection performed better than individual algorithms. This is mainly due to the great switching cost that is incurred between successive algorithm changes at every interval.