ECONOMIC ANALYSES OF PLUG-IN HYBRID ELECTRIC VEHICLES, CARBON MARKETS, AND TEMPERATURE-SENSITIVE LOADS

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This thesis contains three analyses relating to energy and the transition to a low-carbon economy. In Chapter 1, an hourly model is estimated to predict electricity load and price simultaneously. This model is used to calculate how electric vehicles affect electricity markets in New York City and the Hudson Valley for different penetration rates. Charging electric vehicles at night increases the off-peak prices for all customers. The net monthly cost for a PHEV user is about $9 compared to a savings of $115 in gasoline. The extra cost for non-users is only $2. If the feedback effect of load on price is ignored, the extra monthly cost per customer is underestimated by nearly 50%. The costs of PHEV can be reduced substantially by introducing a Vehicle-to-Grid program because it reduces the on-peak prices for all customers and is more than enough to offset the higher off-peak prices.

Chapter 2 determines the optimal energy use portfolio, carbon cap, and carbon shadow price from the Regional Greenhouse Gas Initiative (RGGI) by developing an algorithm to maximize social welfare with a carbon damage cost. By introducing a carbon damage cost, coal and natural gas consumption is reduced over time because the damage from burning fossil fuels increases dramatically over time. The optimum carbon price is determined to be $60/tCO2e compared to the current RGGI price of $2/tCO2e.

Chapter 3 presents the first analysis to use a dynamic structural model to divide the total electricity load into Temperature Sensitive Load (TSL) and Non-Temperature Sensitive Load. (N-TSL). The analysis shows how the system cost can be minimized when controllable thermal storage is used to offset traditional air conditioning demand in New York State and New England. Benefits from reductions in both the energy cost and capacity cost are calculated for thermal storage owners and non-owners. Using only 30% of the TSL, the optimum daily patterns of load and price are effectively flat. However, the main savings are from reducing the peak load, and the associated capacity costs, and not from the lower cost of purchasing electricity.

BIOGRAPHICAL SKETCH

Jung Youn Mo was born in Seoul, South Korea. After entering Korea University, her academic interests broadened when she took an Environmental Economics course in her second year. Topics such as evaluation of environmental value, benefit-cost analysis, and the emission trading system fascinated her and she decided to pursue this field of study at the graduate level. She received her master's degree in Agricultural Economics at Korea University. At that time, as a Research Assistant, she participated in several projects: 'Cost-Benefit Analysis of Greenhouse Gas-Emission Reduction and Long-Run Emission Reduction Scenario Development in Korea', 'Introduction of Emission Trading in Agriculture' and 'Sustainable Development Energy Policy Based on Demand Control'. She has also published a paper, 'The Law of One-price and the Dynamic Relationship between Nord Pool and EU ETS Carbon Price' in the *Journal of Korea Resource and Environmental Economics*, September 2005. Another paper, 'World Emission Allowance Price Analysis' was chosen as the winter of the 2005 Graduate Student Climate Change Thesis Contest held by the Korea Energy Management Corporation. Since joining the Cornell University PhD Graduate Program in order to study energy and carbon emissions, she has extended her research to include the electricity market and is investigating means and solutions to flatten electricity load using Plug-in Hybrid Electric Vehicles and Thermal Energy Storage.

I dedicate this dissertation to my family. Without my parents' support and sacrifice, it would not have been possible for me to complete my researches at Cornell University. Especially, I thank my special friend, Wooyoung, who has helped my research and encouraged me to finish this program.

ACKNOWLEDGMENTS

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I would also like to thank the members of the Engineering and Economics of Electricity research group for providing me with their valuable insight and knowledge. Their members include Tim Mount, Robert Thomas, Richard Schuler, Bill Schulze, Ray Zimmerman, Lindsay Anderson, and Max Zhang.

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CHAPTER 1

PLUG-IN HYBRID ELECTRIC VEHICLES: THE IMPACT OF CHARGING ON THE ELECTRICITY MARKET

1.1 Introduction

In recent years, the U.S. government has been engaged in efforts to reduce carbon emissions and fossil fuel dependence. To accomplish efficient carbon emissions reduction, it is essential to know the main sources of energy consumption since the total amount of Green House Gases (GHGs) emissions is related to the total amount of energy used. Table 1.1 shows energy consumption by sector. In the U.S., the electric utility sector uses roughly 40% of total energy, the transportation sector 30%, the industrial sector 20%, and the residential and commercial sectors 10%**.** Therefore, to reduce carbon emissions in our society, it is essential to reduce the use of fossil fuels by the electric utilities by introducing renewable sources of power generation, and to reduce the amount of gasoline and diesel used by vehicles by switching to electric motors. It should be noted that 25% of overall primary energy is lost as waste heat in the generation of electricity from thermal sources. In addition, another 25% is lost as heat in the transportation sector because internal combustion engines are inherently inefficient.

Chapter 1 focuses on the transportation sector as a starting place for reducing carbon emissions. In this sector, there are several new technologies which have been shown to reduce energy consumption such as liquid biofuels, low temperature fuel cells, and Plug-in Hybrid

Electric Vehicles (PHEVs[1]). Low temperature fuel cells are in need of more technological development before attaining wide-spread use. Likewise, liquid biofuels have a disadvantage in terms of their environmental limitations. Therefore, PHEV are currently the most reasonable option in the effort to reduce carbon emissions in the transportation sector.

Table 1.1 Energy consumption in the U.S. in 2009 (unit: quadrillion Btu)

Source	Residential	Commer-cial	Industrial	Transpor-tation	**Total delivered**	Electric power	Total energy
Petroleum	1.16	0.60	7.94	26.52	**36.22**	0.4	36.62
Natural gas	4.87	3.20	7.50	0.68	**16.25**	7.06	23.31
Coal	0.01	0.06	1.32	0.00	**1.39**	18.30	19.69
Renewable	0.43	0.11	1.42	0.00	**1.96**	3.89	5.85
Nuclear	0.00	0.00	0.00	0.00		8.35	8.35
Total primary	**6.47**	**3.97**	**18.84**[2]	**27.2**	**56.48**	**38.3**[3]	**94.79**
Electricity							
Delivered	4.65	4.51	3.01	0.02	**12.19**		
Losses	9.96	9.66	6.44	0.05	**26.11**		
Total electric	**14.61**	**14.17**	**9.45**	**0.07**	**38.3**		
Total all energy	**21.08**	**18.14**	**28.29**	**27.27**	**94.78**		

Source: EIA "Annual energy outlook 2011", Table B2, p.159

[1] PHEV are similar to existing hybrid cars. The difference is that PHEV can recharge their batteries from an electric wall outlet.
[2] Includes biofuels and co product(0.66)
[3] Includes net imports

When PHEV are introduced into the transportation system, the associated carbon emissions are reduced according to the PHEV penetration rate. The use of imported oil is also reduced which is significant since the efficiency of energy use in the transportation sector is especially low. When the refining, distribution, and combustion processes are taken into consideration, gasoline is only 13% efficient. On the other hand, electrification in the transportation sector results in 85% energy efficiency when the electricity is generated from renewable sources.

When PHEV use increases in our current transportation system, it affects the traditional electricity market by increasing the electricity load. To run a PHEV, the car battery must be regularly charged. This increases the previous load patterns and results in higher electricity prices. Using this change, the extra cost including the charging battery for PHEV owners and the extra cost for non-PHEV owners could be calculated. Previously the cost has been calculated simply by adopting the current electricity market price used by researchers and industries. This approach does not consider the impact of battery charging demand on price. Therefore, the cost caused by PHEV penetration could be underestimated and inaccurate if the feedback from both load and price is ignored.

The purpose of Chapter 1 is to estimate electricity load and price using a two-step process and to calculate both the PHEV charging cost and the economic benefit of the Vehicle to Grid (V2G) program in New York City (NYC) and the Hudson Valley. If a V2G program is introduced, PHEV car owners can sell extra electricity when prices are high. In this way, both PHEV and non-PHEV car owners can benefit by selling and buying electricity at a reduced price during peak load periods.

Since NYC is a large metropolitan area and the Hudson Valley is a rural area near NYC, we are able to compare the PHEV charging costs and benefits of a V2G program in both a representative metropolitan and rural area.

First, electricity load is estimated using temperature and seasonal patterns. Using the predicted value of electricity load from the first step, the electricity price is estimated in the second step. If the predicted values of load and price are estimated, we can analyze the impact of PHEV in the traditional electricity market. Then, using the changed load and price, the PHEV charging cost is calculated. Finally, the cost benefit of the V2G program is simulated using various PHEV penetration rates.

The data and model for electricity load and price are discussed in Section 1.2. Section 1.3 presents the PHEV charging cost and the V2G benefit using the estimated load and price models from Section 1.2. The conclusions are contained in Section 1.4.

1.2 Model for Electricity load and price

The introduction of PHEV into the commuter market clearly brings about a change in the electricity load that in turn affects electricity price. Therefore, an electricity load and price model is developed for calculating PHEV charging cost. Basically, PHEV charging cost is calculated by (new load - base load) * new price. First, we estimate the electricity load using the Autoregressive Integrated Moving Average (ARIMA) model. Next, using the predicted value of electricity load, the electricity price is estimated.

1.2.1 Model for electricity load

Figure 1.1 shows the plot of hourly electricity load in NYC. This hourly load has distinct yearly, weekly, and daily patterns. First, electricity load has clear one-year and half-year patterns related to increased power demand for cooling in the summer and heating in the winter. Next, the electricity load weekly pattern shows marked increase during the Monday-Friday workweek and is significantly reduced during the weekend. Lastly, load also has a strong daily pattern. The daily load increases during working hours and decreases at night. Notably, the daily load pattern in winter is different from the normal summer load pattern. It increases during work hours but also increases again at night for heating. Therefore, there are two peaks in the daily load in winter. The summer peak is higher than the winter peak and sets the grid requirements for system adequacy.

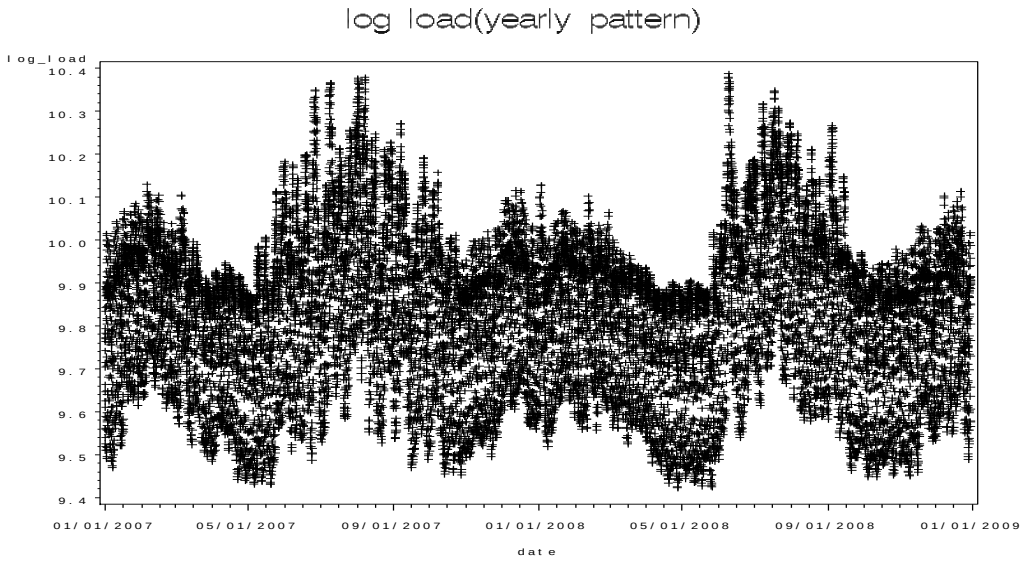

Figure 1.1: Electricity load pattern from 2007 to 2008 (Unit: MWh)

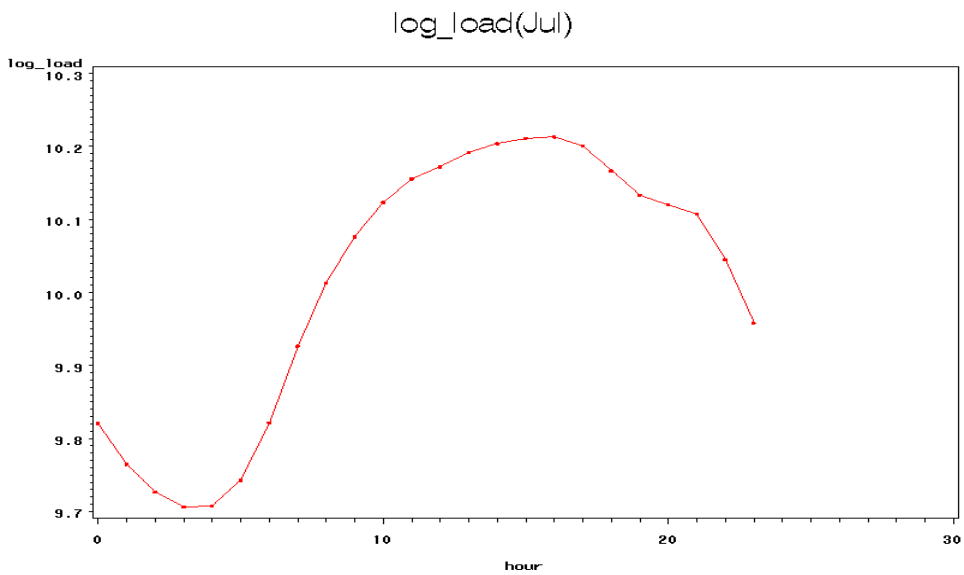

Figure 1.2: Summer electricity load pattern (Unit: MWh)

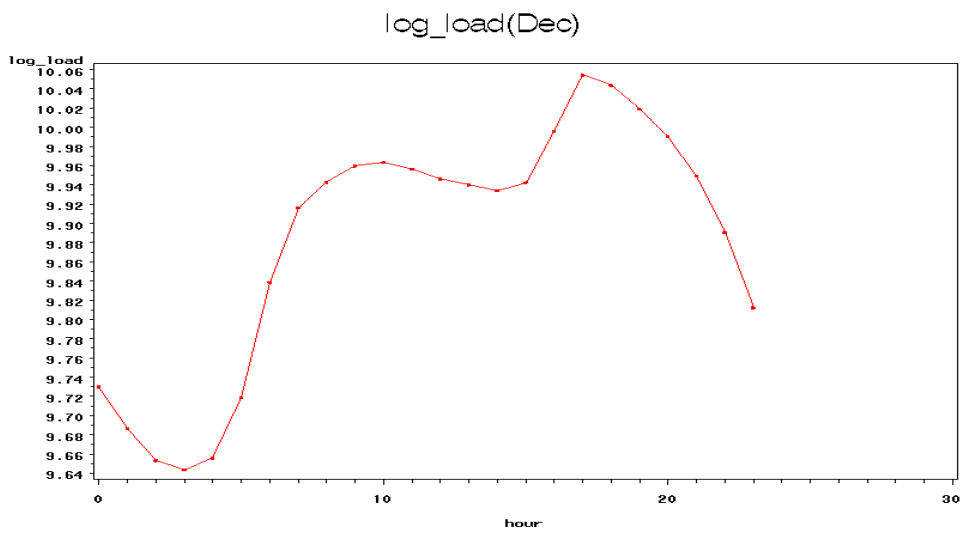

Figure 1.3: Winter electricity load pattern (Unit: MWh)

Load Model

Temperature is the main factor influencing the electricity load. However, raw temperature data cannot explain the load change directly, because loads are affected by high and low

temperature together. To capture this effect, Cooling Degree Days (CDD) and Heating Degree Days (HDD) are introduced in the electricity load model. HDD are defined as follows:

$$HDD = \max(65\text{-temperature}, 0)$$

CDD are defined as follows:

$$CDD = \max(\text{temperature} - 65, 0)$$

The squared CDD and HDD and linear CDD and HDD are included in the model.

Since the load is reduced during weekends and holidays, we add a dummy variable which is zero during the week and one during weekends and national holidays.

Lastly, several sine and cosine curves are used to capture yearly, weekly, and daily patterns. Yearly sine and cosine curves have one-year and half-year cycles. In the case of weekly patterns, three cycles (one-week, half-week, and quarter-week) are added. To capture daily cycles, we add 24-, 12-, and 6-hour-cycle sine and cosine curves. It is found that winter load has a specific pattern. Using this information, a new variable, winter pattern, is created in our model. Winter pattern is one during summer, followed by a cosine curve during winter. Since load pattern is complicated and cannot be represented by these variables alone, the interaction terms among winter pattern, temperature, and cycles are needed to estimate load.

Normally, price affects demand and it is natural to use price as an explanatory variable in the load estimation model. On the other hand, in the electricity market most customers do not confront real-time pricing. They simply pay their electric bills that have been calculated using a fixed regulated price. Under this type of fixed-price system, price cannot explain short-term load behavior. Therefore, our load model does not include price as an explanatory variable.

To summarize, the log for electricity load is a function of time trend, temperature, seasonal patterns, a specific winter pattern, and cross-effect among temperature and patterns.

$$
\begin{aligned}
\log\_load_{it} = {} & \beta_{i0} + \beta_{i1} t_t + \beta_{i2} winter_t + \beta_{i3} c_t + \beta_{i4} s_t + \beta_{i5} c2_t + \beta_{i6} s2_t + \beta_{i7} cw_t + \beta_{i8} sw_t + \beta_{i9} cw2_t + \beta_{i10} sw2_t + \beta_{i11} cw4_t + \beta_{i12} sw4_t \\
& + \beta_{i13} ch_t + \beta_{i14} sh_t + \beta_{i15} ch2_t + \beta_{i16} sh2_t + \beta_{i17} ch4_t + \beta_{i18} sh4_t + \beta_{i19} hol_t + \beta_{i20} cdd_{it} + \beta_{i21} hdd_{it} + \beta_{i22} cdd_{it}^2 + \beta_{i23} hdd_{it}^2 \\
& + \beta_{i24} cdd_t * ch_t + \beta_{i25} cdd_t * ch2_t + \beta_{i26} cdd_t * ch4_t + \beta_{i27} cdd_t * sh_t + \beta_{i28} cdd_t * sh2_t + \beta_{i29} cdd_t * sh4_t \\
& + \beta_{i30} hdd_t * ch_t + \beta_{i31} hdd_t * ch2_t + \beta_{i32} hdd_t * ch4_t + \beta_{i33} hdd_t * sh_t + \beta_{i34} hdd_t * sh2_t + \beta_{i35} hdd_t * sh4_t \\
& + \beta_{i36} winter_t * ch_t + \beta_{i37} winter_t * ch2_t + \beta_{i38} winter_t * ch4_t + \beta_{i39} cw_t * ch_t + \beta_{i40} cw2_t * ch2_t + \beta_{i41} cw4_t * ch4_t \\
& + \beta_{i42} sw_t * sh_t + \beta_{i43} sw2_t * sh2_t + \beta_{i44} sw4_t * sh4_t + \beta_{i45} cy_t * ch_t + \beta_{i46} sy_t * sh_t + \beta_{i47} cy2_t * ch_t + \beta_{i48} sy2_t * sh_t + u_{it}
\end{aligned}
$$

i=1:NYC

$i = 2: Hudson\ valley, Millwood, Dunwood$

$\log\_load_{it} = \log\ of\ \ electricity\ load$

$t_t = time\ trend$

$cy_t, sy_t, cy2_t.sy2_t : yearly\ \ pattern\ \text{variables}(\text{cosine and sine curves with year and half years peroid})$

$cw_t, sw_t, cw2_t, sw2_t, cw4_t, sw4_t : weekly\ \ pattern\ \text{variables}$

$(\text{cosine and sine curves with week, half week, and quarter weeks peroid})$

$ch_t, sh_t, ch2_t, sh2_t, ch4_t, sh4_t : daily\ \ pattern\ \text{variables}$

$(\text{cosine and sine curves with 24 hour, 12 hour, and 6 hours peroid})$

$winter_t : winter\ \ pattern\ (zero\ during\ summer, is\ \ followed\ by\ \text{cosine curve during winter})$

$hol_t = 1\ if\ holiday, otherwise = 0$

$cdd_t,\ hdd_t : heating\ \text{degree days}\ and\ \ cooling\ \text{degree days}$

Table 1.2: Basic data statistics

variables	mean	min	max	std Dev
NYC load(MWh)	6238.43	3988.20	11261.60	1295.35
Hudson valley load(MWh)	2245.31	969.50	4439.60	488.18
NYC price($)	86.60	25.47	373.61	35.75
Hudson valley price($)	79.36	25.05	322.64	29.95
NYC temperature(F)	56.38	11	99	17.87
Hudson valley temperature(F)	51.01	0	93	19.07
natural gas price($)	7.87	0.54	13.32	1.83

In NYC and the Hudson valley area, most coefficients for estimating electricity load are statistically meaningful except for some interaction variables between seasonal cycles and temperature. From the time trend coefficient, we know that the NYC load increases over time

while that of the Hudson Valley decreases. CDD coefficients are statistically meaningful and positive indicating that high temperatures in the summer months increase the electricity load. Although the coefficients of HDD are negative, the quadratic coefficients are positive. There are also interaction terms that affect the load. Overall, the models satisfactorily explain the winter and summer patterns of load with R^2 over 90%.

Table 1.3: Parameter estimates for NYC and the Hudson Valley load

Variables	NYC		Hudson Valley	
	Parameter Estimate	t Value	Parameter Estimate	t Value
Intercept	8.67112	2020.010	7.67039	1610.850
t	0.00000146	15.240	-7.63413E-7	-6.000
cdd*ch	0.00301	19.900	-0.00603	-21.380
cdd*ch2	-0.00114	-8.860	0.00057105	2.850
cdd*ch4	0.00047306	4.050	0.00029614	1.940
cdd*sh	0.00490	29.470	0.00629	21.250
cdd*sh2	0.00215	17.150	0.00264	12.600
cdd*sh4	-0.00035943	-3.090	0.00006029	0.270
hdd*ch	0.00009060	1.190	0.00217	28.820
hdd*ch2	0.00012117	1.670	-0.00073219	-10.580
hdd*ch4	-0.00014675	-2.040	-0.00007645	-0.890
hdd*sh	-0.00085676	-13.080	-0.00047373	-8.780
hdd*sh2	0.00013700	2.430	-0.00044185	-9.190
hdd*sh4	0.00013704	2.500	0.00043889	8.730
winter*ch	-0.01373	-0.740	-0.05873	-3.060
winter*ch2	-0.02424	-10.130	-0.04040	-14.960
winter*ch4	0.01200	5.070	0.01579	5.820
winter	-0.09007	-7.170	-0.12141	-7.550
cw*ch	0.02868	33.440	0.01688	17.550
cw2*ch2	-0.00068159	-0.820	-0.00355	-3.740
cw4*ch4	-0.00041565	-0.500	-0.00023805	-0.110
sw *sh	-0.00545	-6.320	0.00079392	0.400
sw2*sh2	-0.00977	-11.390	-0.01006	-10.250
sw4*sh4	0.00046153	0.510	0.00096680	1.250
cw	-0.04463	-73.470	-0.02931	-41.420
sw	0.04385	71.990	0.02830	42.100

cw2	-0.00307	-4.910	-0.00234	-5.580
sw2	0.03672	60.340	0.02601	38.450
cw4	-0.00660	-10.770	-0.00311	-5.960
sw4	0.00804	13.240	0.00495	7.170
ch	-0.09198	-15.940	-0.10681	-16.710
sh	-0.14515	-103.950	-0.15971	-102.610
ch2	0.03661	29.810	0.05213	40.190
sh2	-0.06545	-54.010	-0.08854	-66.940
ch4	-0.00644	-5.340	-0.01264	-10.010
sh4	-0.00240	-2.030	-0.00656	-5.040
cy *ch	0.00609	0.660	0.03211	3.320
sy *sh	0.00619	6.670	0.01496	14.940
cy2*ch	0.00846	2.150	0.01206	2.860
sy2*sh	0.00439	4.640	0.00613	6.170
cy	0.01965	3.160	0.04435	5.080
sy	-0.02306	-24.860	-0.02430	-28.210
cy2	0.04393	15.900	0.06153	19.450
sy2	0.03040	42.860	0.03741	48.650
hol	-0.12207	-32.440	-0.08522	-20.460
cdd	0.01540	52.750	0.01808	49.950
hdd	-0.00158	-9.680	-0.00127	-8.830
cdd^2	0.00003265	2.570	0.00031954	15.590
hdd^2	0.00008761	25.650	0.00009572	35.200
	Adj R-Sq	0.920	Adj R-Sq	0.911

Because SAS was not able to handle our complicated ARIMA model to estimate load and residual simultaneously, we estimated load first and corrected the autocorrelation problem using ARIMA for residual. However, the computed residuals are correlated through time. A time-series model for the computed residuals was used to correct the autocorrelations. Table 1.4 summarizes the results of an ARIMA (24, 0, 7) model for the computed residuals for the load log in NYC and an ARIMA (24, 0, 5) for the Hudson Valley. These ARIMA models behave well and pass the white noise test.

Table 1.4: ARIMA model estimation results for the electricity load residuals

Variables	NYC		Hudson Valley	
	Parameter Estimate	t Value	Parameter Estimate	t Value
LRE	0.003	1.070	0.002	0.530
MA(1)	-0.624	19.450	-0.954	4.940
MA(2)	1.343	-60.730	1.131	-9.250
MA(3)	0.111	-3.650	-0.705	3.240
MA(4)	-0.372	21.290	0.395	-4.280
MA(5)	1.246	-45.690	-0.094	1.180
MA(6)	-0.713	27.560		
MA(7)	0.516	-20.340		
AR(1)	1.792	-55.090	1.979	10.260
AR(2)	-2.293	-40.400	-2.311	-7.370
AR(3)	1.553	24.890	2.044	5.410
AR(4)	0.205	4.890	-1.343	-4.010
AR(5)	-1.741	-47.590	0.633	2.920
AR(6)	2.234	35.760	-0.165	-1.620
AR(7)	-1.626	-24.550	0.016	0.470
AR(8)	0.752	15.320	0.005	0.160
AR(9)	-0.099	-2.670	0.035	1.120
AR(10)	0.020	0.550	-0.010	-0.300
AR(11)	-0.061	-1.680	-0.009	-0.310
AR(12)	0.016	0.440	-0.011	-0.350
AR(13)	0.046	1.270	0.069	2.230
AR(14)	-0.144	-3.950	-0.094	-2.850
AR(15)	0.139	3.790	0.104	3.060
AR(16)	-0.045	-1.240	-0.079	-2.210
AR(17)	-0.069	-1.900	0.044	1.330
AR(18)	0.057	1.610	-0.039	-1.230
AR(19)	0.032	1.010	0.059	1.880
AR(20)	-0.098	-3.610	-0.056	-1.770
AR(21)	0.037	1.400	0.027	0.880
AR(22)	0.091	3.650	-0.078	-2.700
AR(23)	-0.071	-4.010	0.251	10.160
AR(24)	0.136	13.330	-0.124	-3.720

1.2.2 Model for electricity price

Price Model

Figures 1.4 and 1.5 are the plots for hourly NYC and Hudson Valley electricity prices. These plots are more complicated than those of electricity load movements because there are numerous price spikes and unexpected movements. To estimate electricity price, we have to find other variables that explain the electricity price behavior. First, electricity load is the main factor determining price and there are two ways to estimate the extent of its impact: 1) use actual electricity load as an explanatory variable or 2) use predicted value of load from our previous load model estimation. For Chapter 1, where the main goal is to estimate PHEV charging cost in our economy, the second method is chosen to calculate electricity cost because we have to simulate the price based on the new load. To do this, the adjusted electricity load when PHEV are introduced determines the new price triggered by the load change. Lastly, it is known that the impact of the summer load on electricity price differs significantly from that of the winter load. To capture this difference, a weight is made to distinguish summer and winter loads. The weight follows a logistic distribution.

$$w = \frac{e^{(a+bx)}}{1+e^{(a+bx)}}, \text{ x=temperature}$$

A weight of 0.5 is assumed for a temperature of 65℉, and weight 0.99 for 80℉. Using these assumptions, the two unknowns *a* and *b* are calculated and finally, weighted summer and winter

load are derived. These four linear and quadratic loads for the summer and winter are the main explanatory variables in our electricity price model.

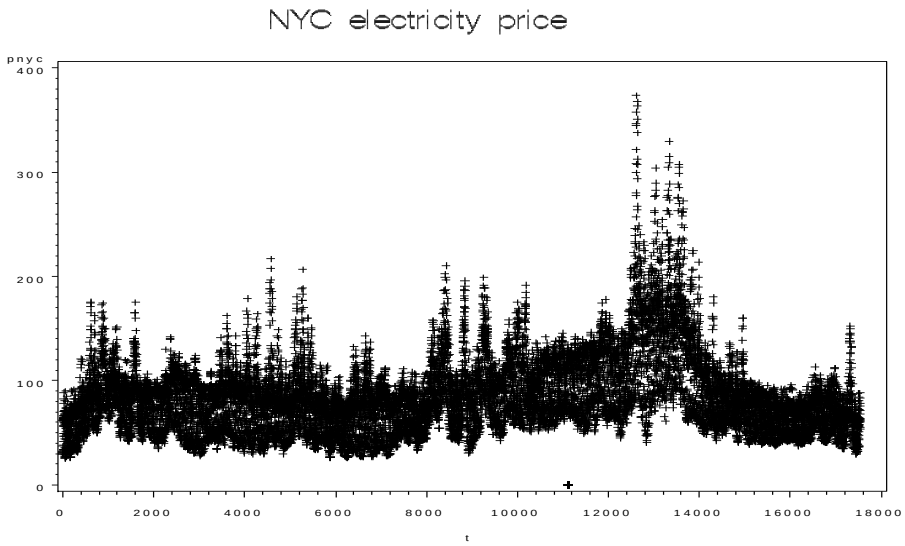

Figure 1.4: NYC electricity price between 2007 and 2008 (Unit: dollars)

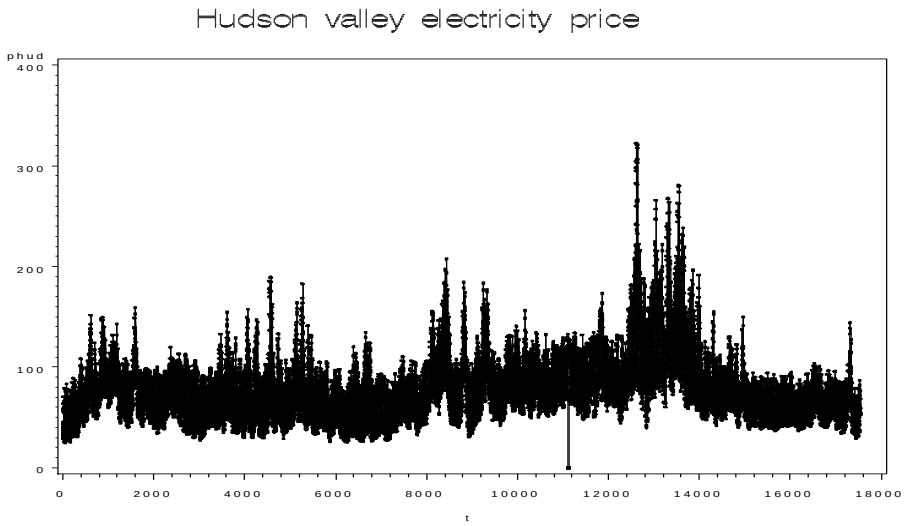

Figure 1.5: The Hudson Valley electricity price between 2007 and 2008 (Unit: dollars)

The price of electricity can also be affected by natural gas prices. In New York State (NYS), in 2009, 31.4% of electricity was generated from natural gas, 9.6% from coal, 2% from oil, 20.7% from hydroelectric conventional, 32.7% from nuclear, and 3.6% from renewable sources. Given that natural gas is a main source for generating electricity especially in NYS where there are numerous gas plants, if natural gas prices increase, so will the cost of generating electricity, a cost that translates into higher electricity prices for the consumer. Since the supply curve for electricity does not respond immediately to changes in the hourly price of natural gas, a finite distributed lag is specified for this price. In other words, current and previous natural gas prices affect the price of electricity because most power plants purchase natural gas in advance. To account for this effect, Lagrange interpolation polynomials for the natural gas price are used to reduce the number of coefficients that have to be estimated. A 2-week (336 hours) period is selected for lag length. Using the Lagrange interpolation polynomials, we eliminate the necessity to estimate 336 coefficients for the 336 different natural gas prices. Instead, we will set up the relationship as a quadratic polynomial that is defined by only three coefficients. In our model, there are three fixed base points (0, 168 = 7*24, and 336 = 14*24) for the beginning, the middle and the end of the lag, and the corresponding three coefficients are estimated using the formulations below for i = 0, 1, 2, … 336. The following three polynomials are generated for the lag structure.

$$w_{31i} = \frac{(i-168)(i-336)}{(0-168)(0-336)}$$

$$w_{32i} = \frac{(i-0)(i-336)}{(168-0)(168-336)}$$

$$w_{33i} = \frac{(i-0)(i-168)}{(336-0)(336-168)}$$

Finally, using these three weights, the following three weighted sums of natural gas prices are calculated for k = 31, 32, and 33:

$$wp_{kt} = \sum_{i=0}^{336} w_{ki} \log PNG_{t-i}$$

In conclusion, the log price of electricity is a function of time trend, predicted value of weighted summer and winter load, weighted natural gas prices, seasonal patterns, a specific winter pattern, and cross effects among yearly, weekly, and hourly patterns.

$$\begin{aligned}
\log_pe_{it} = {} & \beta_{i0} + \beta_{i1} t_t + \beta_{i2} winter_t + \beta_{i3} cy_t + \beta_{i4} sy_t + \beta_{i5} cy2_t + \beta_{i6} sy2_t + \beta_{i7} cw_t + \beta_{i8} sw_t + \beta_{i9} cw2_t + \beta_{i10} sw2_t + \beta_{i11} cw4_t + \beta_{i12} sw4_t \\
& + \beta_{i13} ch_t + \beta_{i14} sh_t + \beta_{i15} ch2_t + \beta_{i16} sh2_t + \beta_{i17} ch4_t + \beta_{i18} sh4_t + \beta_{i19} hol_t + \beta_{i20} wpre_load + \beta_{i21} wpre_load^2 \\
& + \beta_{i22}(1-w) pre_load + \beta_{i23}\left[(1-w) pre_load\right]^2 + \beta_{i24} wp31 + \beta_{i25} wp32 + \beta_{i26} winter_t * ch_t \\
& + \beta_{i27} winter_t * ch2_t + \beta_{i28} winter_t * ch4_t + \beta_{i29} cw_t * ch_t + \beta_{i30} cw2_t * ch2_t + \beta_{i31} cw4_t * ch4_t + \beta_{i32} sw_t * sh_t \\
& + \beta_{i33} sw2_t * sh2_t + \beta_{i34} sw4_t * sh4_t + \beta_{i35} cy_t * ch_t + \beta_{i36} sy_t * sh_t + \beta_{i37} cy2_t * ch_t + \beta_{i38} sy2_t * sh_t + u_{it}
\end{aligned}$$

$\log\_pe_{it} = \log of\ electricity\ price$
$wpre\_load = predicted\ value\ of\ summer\ electricity\ load$
$(1-w) pre\_load = predicted\ value\ of\ winter\ electricity\ load$
$wp31\ and\ wp32 : weighted\ natural\ gas\ prices$

Table 1.5 summarizes the electricity price estimation results for NYC and the Hudson Valley. As we know, the seasonal patterns in price are weaker than those in the load estimation model. Therefore, several seasonal patterns, especially weekly, are not statistically meaningful. The summer and winter electricity supplies have a positive influence on price. From the summer and winter load coefficients, it is found that price elasticity on the summer and winter electricity supply in the Hudson valley is larger on average than it is in NYC. In the case of natural gas prices, it is concluded that the nearest lag coefficient has the most powerful effect on the price of electricity as expected. Overall, the models explain electricity price reasonably well with R^2 over 80%.

Table 1.5: Parameter estimates for NYC and Hudson Valley electricity prices

Variable	NYC		Hudson Valley	
	Parameter Estimates	t Value	Parameter Estimates	t Value
Intercept	-6.70683	-28.490	-4.52252	-30.700
t	-0.00000422	-10.240	-0.00000177	-4.010
winter*ch	0.14940	2.840	0.25720	5.200
winter*ch2	-0.06065	-12.840	-0.03097	-6.700
winter*ch4	0.03133	6.690	0.03005	6.760
winter	-0.30936	-7.640	-0.28726	-8.260
cw*ch	0.00617	2.040	0.01622	6.660
cw2*ch2	-0.00576	-2.230	-0.00423	-1.730
cw4*ch4	0.00076418	0.290	0.00051673	0.130
sw*sh	-0.00016221	0.010	-0.00705	-2.760
sw2*sh2	-0.00388	-1.430	-0.00117	-0.560
sw4*sh4	0.00325	1.270	0.00258	0.950
cw	0.01066	6.230	-0.00364	-1.810
sw	-0.00109	-0.320	0.01186	7.190
cw2	0.00178	1.470	0.00051024	1.630
sw2	0.00497	2.210	0.01061	6.040
cw4	0.00002520	0.150	-0.00052135	0.490
sw4	0.00513	2.620	0.00401	2.240
ch	-0.09394	-5.430	-0.12724	-7.930

sh	-0.09061	-19.950	-0.02727	-6.530
ch2	0.00976	3.540	-0.00579	-2.630
sh2	-0.06858	-27.960	-0.02177	-7.890
ch4	-0.01094	-4.640	-0.00194	-0.840
sh4	0.01551	8.630	0.02150	12.600
cy *ch	-0.07719	0.027	-0.11447	-4.600
sy*sh	0.01338	5.240	0.01023	4.080
cy2*ch	-0.01345	-1.190	-0.04204	-3.920
sy2*sh	-0.00116	-0.520	0.00361	1.460
cy	0.30656	15.420	0.21458	11.900
sy	0.08540	28.680	0.05216	19.980
cy2	0.05461	5.620	0.02881	3.250
sy2	-0.02915	-12.460	-0.04027	-18.740
hol	-0.05475	-4.490	-0.05931	-5.390
$wpre\_load^2$	0.01334	7.180	-0.01006	-6.330
wpre_load	1.07899	38.830	1.15151	49.860
$[(1\text{-}w)pre\_load]^2$	-0.01092	-5.200	0.01497	8.250
(l-w)pre_load	1.28445	35.710	0.94996	39.100
wp31	0.00118	18.920	0.00102	18.120
wp32	0.00074112	25.670	0.00060040	23.600
	Adj R-Sq	0.812	Adj R-Sq	0.797

As in the previous load estimation model, we cannot run simultaneous ARIMA for electricity prices based on a complicated residual structure with many explanatory variables for price. Hence, a two-step ARIMA is estimated for electricity price. Electricity price is estimated first and the residuals from this regression are computed and used as the dependent variable in the second step to estimate an ARIMA. Table 1.6 summarizes the results of an ARIMA (24, 0, 5) model for the computed residuals for the log price of electricity in NYC and an ARIMA (24, 0, 5) for the Hudson Valley price residual. Both residuals passed the white noise test and are well behaved.

Table 1.6: ARIMA model estimation results for the electricity price residuals

Variables	NYC		The Hudson Valley	
	Parameter Estimate	t Value	Parameter Estimate	t Value
LRE	0.774	14.840	0.038	2.310
MA(1)	0.700	-38.970	0.720	-47.680
MA(2)	0.672	-41.630	0.682	-47.340
MA(3)	0.450	-22.590	0.462	-26.220
MA(4)	0.328	-20.350	0.328	-22.860
MA(5)	0.179	-11.050	0.177	-12.710
AR(1)	0.185	11.300	0.150	11.370
AR(2)	-0.101	-5.700	-0.109	-7.770
AR(3)	0.087	4.710	0.079	5.400
AR(4)	0.087	1.180	0.017	1.240
AR(5)	0.051	3.060	0.038	2.880
AR(6)	0.107	7.970	0.089	8.120
AR(7)	0.011	1.540	0.009	1.250
AR(8)	0.050	7.240	0.040	6.000
AR(9)	0.040	5.670	0.032	4.810
AR(10)	0.023	3.350	0.022	3.360
AR(11)	0.018	2.510	0.023	3.540
AR(12)	-0.023	-3.240	-0.023	-3.430
AR(13)	0.013	1.810	0.015	2.210
AR(14)	-0.008	-1.160	-0.005	-0.820
AR(15)	0.000	-0.060	0.002	0.330
AR(16)	-0.007	-1.020	-0.013	-2.020
AR(17)	0.011	1.640	0.012	1.770
AR(18)	0.010	1.450	0.001	0.130
AR(19)	-0.001	-0.140	-0.011	-1.740
AR(20)	-0.002	-0.240	-0.007	-1.120
AR(21)	0.010	1.450	0.008	1.180
AR(22)	-0.047	-6.790	-0.071	-10.870
AR(23)	0.083	11.670	0.067	9.860
AR(24)	0.467	60.950	0.539	75.450

1.3 PHEV charging cost and V2G program

1.3.1 PHEV charging cost

To calculate PHEV charging cost in NYC and the Hudson Valley, it is first necessary to find out how the electricity load changes when PHEV are introduced to the system. The change in electricity load depends on the PHEV penetration rate and charging scenarios. To calculate the total charge needed for PHEV, the same procedure used by Corey White was adopted to analyze data on commuting patterns reported in the National Household Transportation Survey. The drivers are separated into five categories depending on the number of miles driven each day: 0-10, 10-20, 20-30, 30-40, and over 40. Next, it is assumed that everyone in a bin drives the mean number of miles for that category and that each mile in a PHEV uses 0.2 KWh of electricity[4]. The required electricity can be calculated for each group of drivers (the mean miles of each category * 0.2 KWh/mile). Finally the total required electricity for charging is calculated for a given penetration of PHEV using the formulation below.

Total electricity (MWh) required for group i = (PHEV penetration rate* total number of commuters[5] *percentage of drivers in group i*KWh required for group i)/1000

Lastly, it is assumed that each driver will charge their PHEV at night from 12AM to 6AM. In fact, there is a long range of time for charging a PHEV battery. Car owners could charge as soon as they return home. However, it is assumed that car owners are cost-conscious and want to minimize their charging expense. Under this assumption, charging the battery during non- peak times from 12AM to 6AM is the best strategy.

[4] Battery capacity is 8KWh. A full battery charge allows for 40 miles of driving.
[5] Total number of commuters in NYC = 1,130,002 and in The Hudson valley=1,264.

Table 1.7: The total electricity charge in NYC for 10% PHEVs penetration rate

Category	% of Drivers	Average Miles Driven	KWh Required/Vehicle	Total Electricity(MWh) Required for 10% Penetration
0-10 miles	0.22	4.38	0.88	21.96
10-20 miles	0.20	14.84	2.97	68.14
20-30 miles	0.21	25.33	5.07	118.56
30-40 miles	0.14	33.61	6.72	105.96
0ver 40 miles	0.23	59.39	8.00*	206.56
Total				521.18

* The maximum electric range is 40 miles

To show the new daily load and price profile based on the different PHEV penetration rate, we choose the normal summer day (07/05/2007) and plot the data. Figure 1.6 shows the new electricity load plots for different PHEV penetration rates. If drivers are economy-minded, they want to minimize their charging cost and will charge their batteries when the electricity price is low. If the electricity load is changed because of PHEV penetration, the electricity price will be affected. Figure 1.7 shows the new electricity price plots. Figure 1.7 shows that electricity prices increase at night and that the price range is reduced when PHEV are introduced in NYC. Similar calculations can be done for the Hudson Valley.

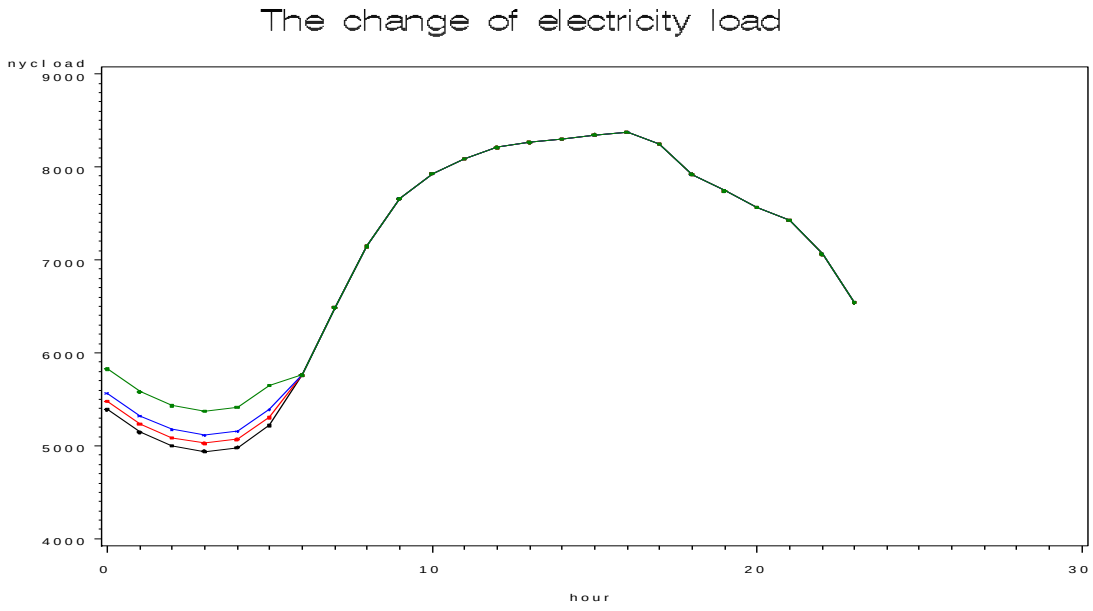

Figure 1.6: Electricity load change on 7/05/2007 (Unit: MWh)

(Black=baseline, Red=10% PR[6], Blue=25% PR, Green =50% PR)

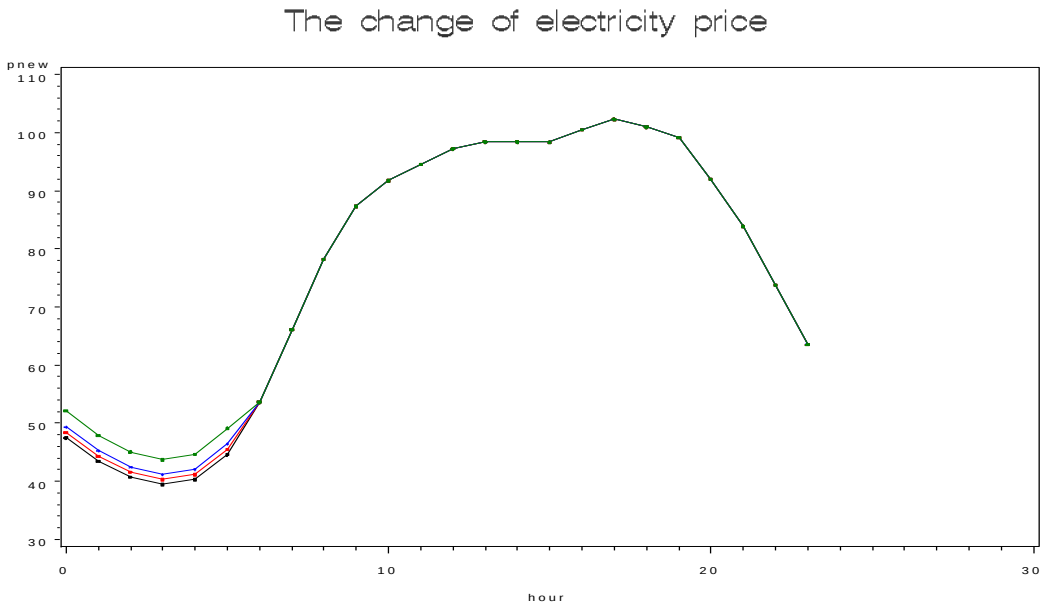

Figure 1.7: Electricity price change on 7/05/2007 (Unit: dollars)

(Black=baseline, Red=10% PR, Blue=25% PR, Green =50% PR)

[6] PR=Penetration Rate

Using the estimated electricity load and price models, the total costs of purchasing electricity are calculated in NYC and the Hudson Valley for all days in 2007 and 2008, and these totals are divided by 24 to give the costs for an average month. Given that the penetration of PHEVs into the market causes additional costs due to changes in the electricity load and price, we first calculate the average monthly increase in the cost of baseline purchases caused by the increased off-peak price for both PHEV users and non-PHEV users. Second, the average monthly cost of charging a PHEV Battery is calculated for a PHEV user. Finally, average extra monthly costs for both types of consumers are derived.

Next, the total number of customers is divided into PHEV users and non-PHEV users. The numbers of PHEV users are determined by the different PHEV penetration rates. In the case of NYC, the total number of customers is 2,709,844[7] and the number of PHEV users is 1,130,002*PHEV penetration rate. The Hudson Valley's customer number is 2,225[8] and the PHEV users number is 1,264*PHEV penetration rate. The non-PHEV users always consume the baseline amount of electricity. The PHEV users also use the baseline amount plus the electricity needed to charge their PHEV batteries. By charging their PHEV batteries during non-peak hours, PHEV users increase the system load and effectively raise the market price at night for all customers. The extra costs for both non-PHEV users and PHEV users can be calculated as below.

[7] This is Consolidated Edison's customers number in 2005.
[8] We can't get the exact customers number in The Hudson valley area. Therefore, using the population ratio between NYC and the Hudson valley and NYC's customers number, we estimate the total customers number in the Hudson valley.

1) Average Monthly Increase in the Cost of Baseline Purchases = $\sum_{i=1}^{17520}$ Base load$_i$*(New price$_i$ - Base price$_i$)/(2*12* Total number of customers)

2) Average Monthly Cost of Charging a PHEV Battery = $\sum_{i=1}^{17520}$ (New load$_i$ - Base load$_i$)*New price$_i$/ (2*12* Number of PHEV users)

Extra monthly cost for a PHEV non-user = (1)

Extra monthly cost for a PHEV user = (1) + (2)

Table 1.8: Average extra monthly cost for different PHEV penetration rates

	NYC		Hudson Valley	
	PHEV owner	Non-PHEV owner	PHEV owner	Non-PHEV owner
	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)
PR=10%	9.29	0.30	9.34	0.27
PR=25%	9.94	0.78	10.04	0.69
PR=50%	10.97	1.54	11.32	1.45

Table 1.8 shows the resulting extra monthly cost in NYC and the Hudson Valley. The cost increases as the penetration rate goes up,and if the PHEV penetration rate is over 25%, the increase of the cost is even greater. Generally, the extra monthly cost in NYC is from $9.29 to $10.97 per month for a PHEV user and only from $0.30 to $1.54 per month for a PHEV non-user.

In the Hudson Valley, the extra monthly cost is from \$9.34 to \$11.32 per month for a user and from \$0.27 to \$1.45 per month for a non-user. All of these increases are relatively small, and for a PHEV user in NYC, the savings in the cost of gasoline of about \$115 per month[9] is substantially larger.

If the extra monthly cost per customer is calculated using the base price by assuming there is no feedback from the new increased load, the cost is biased and underestimated. To determine the feedback effect of load on price and compare the extra monthly costs per customer, the two different extra monthly costs are calculated as follows:

Average extra monthly cost per customer based on the new price = $[\sum_{i=1}^{17520}$ Base $load_i$*(New $price_i$ - Base $price_i$)+(New $load_i$ - Base $load_i$)*New $price_i]$/(2*12* Total number of customers)

Average extra monthly cost per customer based on the base price = $[\sum_{i=1}^{17520}$ (New $load_i$ - Base $load_i$)*Base $price_i]$/(2*12* Total number of customers)

The results in Table 1.9 show that the extra monthly cost per customer is underestimated by nearly 50% of the correct cost.if the feedback effect of higher demand on price is ignored. With higher PHEV penetration rates, the percentage bias is also higher. The overall conclusion is that

[9] The average number of miles driven in Table 1.7 is 23/ day and, assuming the vehicle get 24 miles/gallon and gasoline costs \$4/gallon, the monthly savings is \$23*4*30/24 = \$115/month.

it is important to consider the feedback effect of load on price to calculate the extra monthly cost per customer accurately.

Table 1.9: Average extra monthly cost per customer by different price regime

	NYC			Hudson valley		
	Calculation based on new price(A)	Calculation based on base price(B)	(B/A)* 100	Calculation based on new price(A')	Calculation based on base price(B')	(B'/A')* 100
	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	(%)	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	(%)
PR=10%	0.69	0.37	53.62	0.70	0.39	55.44
PR=25%	1.74	0.93	53.45	1.77	0.96	54.15
R=50%	3.51	1.85	52.71	3.65	1.93	52.90

1.3.2 V2G program benefit

The Vehicle to Grid (V2G) program is described as a system in which plug-in hybrid electric vehicles are connected with the power grid to sell demand response services by delivering electricity into the grid to reduce the daily peak load. Since most vehicles are parked 95 percent of the time, their batteries could be used to let electricity flow from the car to the power system if the electricity price is high enough. Therefore, PHEV can be a new source of peak electricity in the system and reduce peak load during the day. One problem inherent in the electricity market is the large daily range of load and price. Introducing a V2G program can reduce both the peak electricity load and price effectively. At the same time, the amount of

electricity purchased at night to charge the batteries increases with a corresponding increase in the off-peak price. Under this V2G program, it is assumed that all PHEV users charge their battery fully at night and sell extra electricity when the price is high. Using the money gained from selling the electricity, the PHEV users reduce their extra monthly cost. In case of non-PHEV users, they also reduce their extra monthly cost from the reduced peak price caused by PHEV owners who participate in a V2G program.

In this section, we want to simulate the extra monthly cost based on the introducing V2G program under various PHEV penetration rates. The basic method used to calculate the extra monthly cost under a V2G program is as same as the previous case which the PHEV battery is charged without a V2G program. The Average extra monthly cost under the V2G program for a PHEV owner and a non-PHEV owner is presented as below.

1') Average Monthly Increase in the Cost of Baseline Purchases = $\sum_{i=1}^{17520}$ Base $load_i$*(New $price_i$ - Base $price_i$)/ (2*12* Total number of customers)

2') Average Monthly Cost of Charging a PHEV Battery = $\sum_{i=1}^{17520}$ (New $load_i$ - Base $load_i$)*New $price_i$/ (2*12* Number of PHEV owners)

Extra monthly cost for a non-owner = (1')

Extra monthly cost for an owner = (1') + (2')

To estimate the new electricity load under the V2G program, an hourly measure of vehicle availability is assumed. Data from the Regional Travel – Household Interview Survey (RT-HIS) in the New York Metropolitan Area is used to calculate the percentage of commuter vehicles that

are parked and available for V2G each hour (NYDOT, 2000). Using the hourly measure of vehicle availability and the PHEV penetration rate, the new load and price under a V2G program be can be simulated. Figures 1.8 and 1.9 show the new load and price profiles, respectively. Comparing these figures with Figures 1.6 and 1.7 above demonstrates the lower load and price on-peak and the higher load and price off-peak.

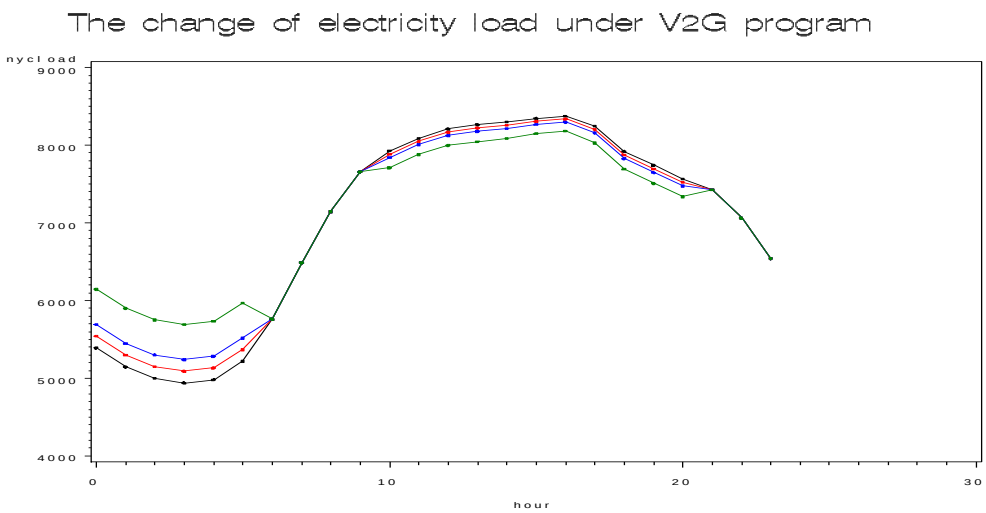

Figure 1.8: Electricity load change under a V2G program on 7/05/2007 (Unit: MWh)

(Black=baseline, Red=10% PR, Blue=25% PR, Green =50% PR)

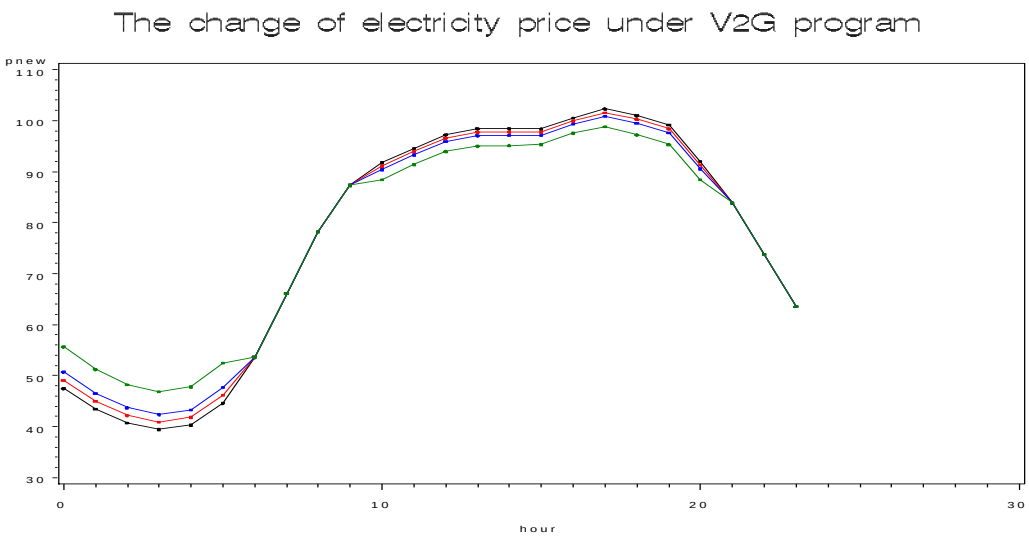

Figure 1.9: Electricity price change under a V2G program on 07/05/2007 (Unit: $/MWh)

(Black=baseline, Red=10% PR, Blue=25% PR, Green =50% PR)

Table 1.10: Extra monthly cost under the V2G program

	NYC		Hudson Valley	
	One PHEV owner	One non-PHEV owner	One PHEV owner	One non-PHEV owner
	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)	Average Monthly Cost (dollars)
PR=10%	1.29	0.09	1.30	0.09
PR=25%	1.93	0.18	1.98	0.21
PR=50%	2.91	0.30	3.11	0.36

The extra monthly costs under a V2G program are summarized in Table 1.10. With a V2G program, the PHEV users get the benefit from selling electricity when the price is high. Using this money, they reduce their net monthly cost. First, comparing the extra monthly cost for a PHEV user in NYC and the Hudson valley, the net cost is smaller in NYC than than it is is the Hudson Valley. The commuters in NYC have shorter commuter distances than the Hudson valley, and therefore, NYC commuters have more electricity to sell in a V2G program and they gain more money.. Comparing the effects for non-PHEV users, the extra monthly costs are all very small and slightly smaller in NYC.

Finally, comparing the extra costs for a PHEV owner with and without a V2G program in Tables 1.8 and 1.10, the extra monthly cost is reduced substantially by about 80% with a V2G program. The benefit from selling electricity at the peak price, offsets the extra monthly cost caused by higher purchases at off-peak prices. If we consider the overall benefit from a V2G program, the net monthly cost of roughly $2 for a PHEV user is very small compared to the $115 average savings in gasoline. Hence, it is concluded that a V2G program provides a strong incentive for a PHEV user to participate, particularly in NYC where commuting distances are relatively small.

1.4 Conclusion

Transportation is the second biggest source of carbon emissions in the U.S. To reduce carbon emissions efficiently and economically, it is essential to reduce those caused by the

transportation sector. From this standpoint, PHEV are a promising means by which to decrease carbon emissions from the transportation sector and also to reduce reliance on imported oil if the electricity is generated from renewable sources, As more and more PHEV are introduced into the economy, the traditional electricity market will also be affected. The increased demand for electricity required to charge the PHEV battery will change the current electricity load resulting in corresponding changes in the electricity market price.

To analyze the impact of PHEV on the electricity market and to calculate the PHEV charging cost in NYC and the Hudson Valley, a two-step process was developed to estimate a dynamic structural model of the electricity load and price. First, the hourly electricity load was estimated using temperature and seasonal patterns represented by yearly, weekly, and daily sine and cosine curves, and a time trend. From this estimation, the predicted values of the electricity load were estimated. Second, the electricity price in NYC and the Hudson Valley were estimated using the predicted value of load. Electricity price is defined as a function of the load, natural gas prices, seasonal patterns, and a time trend. It was concluded that electricity load is the most important factor determining the electricity price and that current and lagged prices of natural gas affect the price through a polynomial distributed lag.

Finally, using the electricity load and price model, the extra monthly cost is calculated for NYC and the Hudson Valley. When PHEV are introduced into the transportation system, there is a resulting increase in electricity load when PHEV batteries are charged at night. The changed load, in turn, increases the off-peak price of electricity for all customers. Hence, the extra monthly cost caused by introducing PHEV is analyzed based on the new electricity load and

price. Customers are divided into two types, PHEV users and non-PHEV users, and the extra monthly costs are calculated for both types of customer. For non- PHEV users, the electricity price is still increaseded by the PHEV users' charging behavior. Therefore, it is interesting to consider the two different types of customer and compare their costs. In sum, the extra monthly cost for an average PHEV owner in NYC is $9.94 per month when the PHEV penetration rate is 25% and $10.14 per month in the Hudson Valley. The lower cost in NYC reflects the lower commuting distances compared to the Hudson Valley. The extra costs for non-PHEV usrs are very small and only $0.78 per month in NYC and $0.69 per month in the Hudson Valley. . If the PHEV penetration rate is increased from 25% to 50%, the monthly costs go up rapidly.

The analysis in Chapter 1 is the first one to calculate the extra monthly cost per customer based on the feedback of load on price using a dynamic structural model. If we ignore the increased load effect on the price, the cost is biased and underestimated by nearly 50% of the correct charging cost. Therefore, it is essential to consider the load and price feedback effect to calculate the extra monthly cost per customer accurately.

If a V2G program is added to the system, selling the stored electricity that is not needed for transportation can reduce the peak electricity load and the price. At the same time, the load for charging the batteries at night increases. Consequently, the daily range of electricity load and price decreases. Overall, PHEV users reduce their net monthly cost dramatically. In addition to the PHEV users, non-PHEV users also gain because the reduced peak price, when their load is high, is more than enough to offset the extra cost from the increased off-peak price, when their demand is low. The overall conclusion is that the reduced net monthly cost for PHEV users with

a V2G program provides a strong incentive for PHEV users to participate. However, even with a high penetration of PHEV and a V2G program in place, the total battery capacity is not big enough to make substantial reductions in the peak load. To reduce system peak load substantially, it will be necessary to develop other bigger storage systems and use them together with the PHEV. Chapter 3 shows how the use of thermal storage to replace air-conditioning can provide sufficient storage capacity to completely flatten the daily load cycle.

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CHAPTER 2

OPTIMAL CARBON EMISSION PRICE IN REGIONAL GREENHOUSE GAS INITIATIVE (RGGI[10])

2.1 Introduction

To reduce carbon emissions from power plants, 10 states (New York, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, Rhode Island, and Vermont) agreed to decrease greenhouse gas emissions starting in 2009 and devised a cap and trade system, the Regional Greenhouse Gas Initiative (RGGI). In the case of NYS, annual emissions of carbon dioxide from New York power plants are capped at 64 million tons from 2009 through 2014. From 2015 on, the cap will be reduced by 2.5 percent per year.

[10] The RGGI is the first mandatory cap and trade market in the United States designed to reduce greenhouse gas emissions from power generations. Ten states have established a cap and will reduce power sector CO_2 emissions 10 percent by 2018.

The most serious criticism of the RGGI is the cap's ceiling. It is asserted that the current cap is greater than the expected carbon emission level from power plants. If the cap is not effective, therefore, the carbon market will not work well. Under the current cap, many economists expect that the future carbon price will be $2/ton in 2012. This is not an appropriate price for reducing carbon emissions. In Europe, carbon price converged to almost zero in the first year because of too soft a cap. If the future carbon price reaches $2/ton, it will be difficult to increase renewable energy sources based on a relative carbon price advantage. Therefore, a low-carbon economy cannot be achieved via the carbon emissions market alone. It is essential to estimate optimal cap quantity and carbon price while taking carbon damage and reduction cost into consideration.

2.2 Discrete time maximization problem

First, it is necessary to estimate the optimal carbon emission price for the RGGI emission market. To calculate this optimal level, a social welfare maximization problem is developed to consider the utility from the consumption of energy and carbon emissions damage cost in our economy. Using this maximization model, the optimal mixture of energy use and optimal carbon emissions level are estimated.

It is assumed that there are three sources for generating electricity (y1 = electricity from coal, y2 = electricity from natural gas, and y3 = electricity from wind energy). y1 and y2 create carbon emissions. The electricity generation from y3 is totally different from traditional fossil

fuel energies whose supply quantities are known. Wind energy in contrast depends on the unpredictable existence of wind and the changeable speed at which it blows. The variability of such factors means that electricity generation from this renewable source cannot be controlled. Hence, it is assumed that electricity from wind is determined from outside of our maximization model and it is followed by Weibull distribution. The cost of electricity production is also assumed to be $c_i(y_i)=a_i+b_iy_i+\frac{1}{2}c_iy_i^2$. Lastly, it is defined that the carbon damage function is quadratic and depends on the total carbon emissions stock in the air.

$$\underset{\{y_1,y_2\}}{\text{Maximize}}\ \pi=\sum_{t=0}^{T}\rho^t\left[(y_{1,t}+y_{2,t}+y_{3,t})^{(1-\varepsilon)}/(1-\varepsilon)-\sum_i c_i(y_{i,t})-f(C_t)\right]$$

Subject to

$$C_{t+1}-C_t=-\theta C_t+\sigma_1 y_{1,t}+\sigma_2 y_{2,t}$$

$$C(0)=C_0$$

$y_{3,t}\ \square\ W(k,c,p)$, where $y_{3,t}$ is an iid random variable

Where, $c_i(y_{i,t})=a_i+b_iy_{i,t}+\frac{1}{2}c_iy_{i,t}^2\quad i=1,2$

f(C)= $\frac{1}{2}dC^2$, where f(C) is carbon damage function

$$\rho=\frac{1}{1+\delta},\quad where\ \delta=discount\ rate$$

y3 is a random variable and depends on the wind speed. Finally wind speed is characterized by Weibull distribution.

The wind speed probability density function can be calculated as

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left(-\left(\frac{v}{c}\right)^{k}\right)$$

Where, c is the Weibull scale parameter and k is the dimensionless Weibull parameter. If we know the mean ($\bar{v}$) and variance (σ^2), we can calculate k and c.

$$k = \left(\frac{\sigma}{\bar{v}}\right)^{-1.086}$$

$$c = \frac{\bar{v}}{\Gamma(1+1/k)}$$

Where, $\Gamma(x) = \int_0^\infty e^{-u} u^{x-1} du$ (gamma function)

Then, the average wind energy can be expressed as

$$E\{y_3\} = \frac{\rho A v^{-3} \Gamma(1+3/k)}{2\Gamma(1+1/k)^3}$$

Where, ρ is the density of the wind and A is the windswept area (Air density of 1.225 kg/m^3 at 15°C, A=n D^2/4, where D is the rotor diameter in feet.) Assume that: the rotor is 6.7 meters (22 ft) in diameter, A is 11.22, wind speed is 7.5, height above ground is 50m., roughness length is 3, and shape parameter is 2.

To solve this dynamic optimization problem, we have to solve the current value Hamiltonian (H_t). If we check the equations below, it is found that it is impossible to arrive at closed form solutions because of the nonlinearity of equations. To handle this nonlinearity problem, an algorithm which can solve this dynamic optimization problem is developed.

$$H_t = (y_{1,t} + y_{2,t} + y_{3,t})^{(1-\varepsilon)} / (1-\varepsilon) - \sum_i c_i(y_i) - \frac{1}{2} d C_t^{\,2} + \rho\lambda_{t+1}(-\theta C_t + \sigma_1 y_{1,t} + \sigma_2 y_{2,t})$$

$$\frac{\partial H_c}{\partial y_{i,t}} = 0 \ \forall\ i, \ \ -\frac{\partial H_t}{\partial C_t} = \rho\lambda_{t+1} - \lambda_t, \ \frac{\partial H_c}{\partial \rho\lambda_t} = C_{t+1} - C_t$$

$$(y_{1,t} + y_{2,t} + y_{3,t})^{-\varepsilon} - (b_1 + c_1 y_{1,t}) + \sigma_1 \rho\lambda_{t+1} = 0 \qquad (1)$$

$$(y_{1,t} + y_{2,t} + y_{3,t})^{-\varepsilon} - (b_2 + c_2 y_{2,t}) + \sigma_2 \rho\lambda_{t+1} = 0 \qquad (2)$$

$$\rho\lambda_{t+1} - \lambda_t = -\left[-dC_t - \rho\lambda_{t+1}\theta\right] \qquad (3)$$

$$C_{t+1} - C_t = -\theta C_t + \sigma_1 y_{1,t} + \sigma_2 y_{2,t} \qquad (4)$$

First, an initial value for λ_0 is randomly presumed. Using this initial value, $\rho\lambda_{t+1}$ is calculated and used in equations (1) and (2) as a constant. If we solve two nonlinear equations (1) and (2), we can determine the next period carbon emission stock (C_{t+1}) using $y_{1,t}$ and $y_{2,t}$. From equation (3), we can arrive at the next period carbon shadow price λ_{t+1} using C_{t+1}. We repeat this procedure until the period is T and then calculate the cumulated social welfare. If the

initial value presumed for λ_0 maximizes the cumulated social welfare, we stop. Otherwise, we repeat this procedure using different initial values for λ_0 until the optimal value for λ_0 is found.

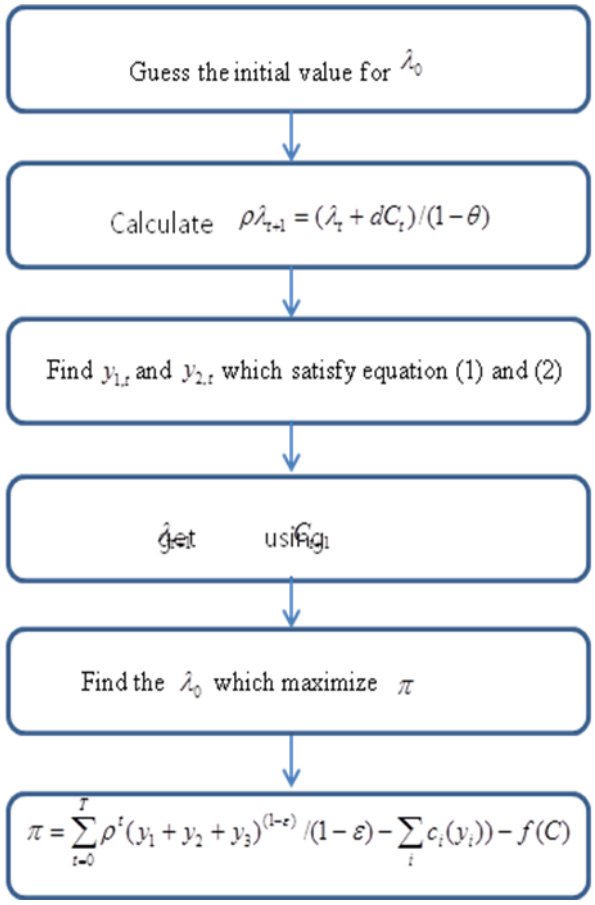

Figure 2.1: Algorithm

2.2.1 Parameter estimation

First, the cost function for electricity from coal and natural gas are estimated using PJM data from 2009. Table 2.1 summarizes the results.

Table 2.1 Cost function estimation results

Variables	Coal Cost Function		Natural Gas Cost Function	
	Parameter Estimate	t Value	Parameter Estimate	t Value
Intercept	7949.374	7.050	-15398	-5.590
y	14.306	77.470	42.334	152.410
y^2	3.0491E-04	46.660	3.0625E-04	54.130
	Adj R-Sq	0.9992	Adj R-Sq	0.9997

Results from Richard S. J. Tol[11] are used for capturing the carbon damage function parameter. The calculated marginal damage of carbon emission is $16/tC and current carbon emission concentration is 387ppm. (=387*2.13*10^9*44/12tCO2e). Therefore, d= ($16/ (387*2.13*10^9*(44/12) ^2) tCO2e)

ε =0.32

θ =0.024 (Richard Houghton, Senior Scientist, Carbon Research)

ρ =1/ (1+0.02) =0.9804

[11] 2005, The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties, Energy Policy, Volume 33, Issue 16

σ_1 =0.955(tCO2/MWh)

σ_2 =0.597(tCO2/MWh)

2.3 Results

2.3.1 Baseline results

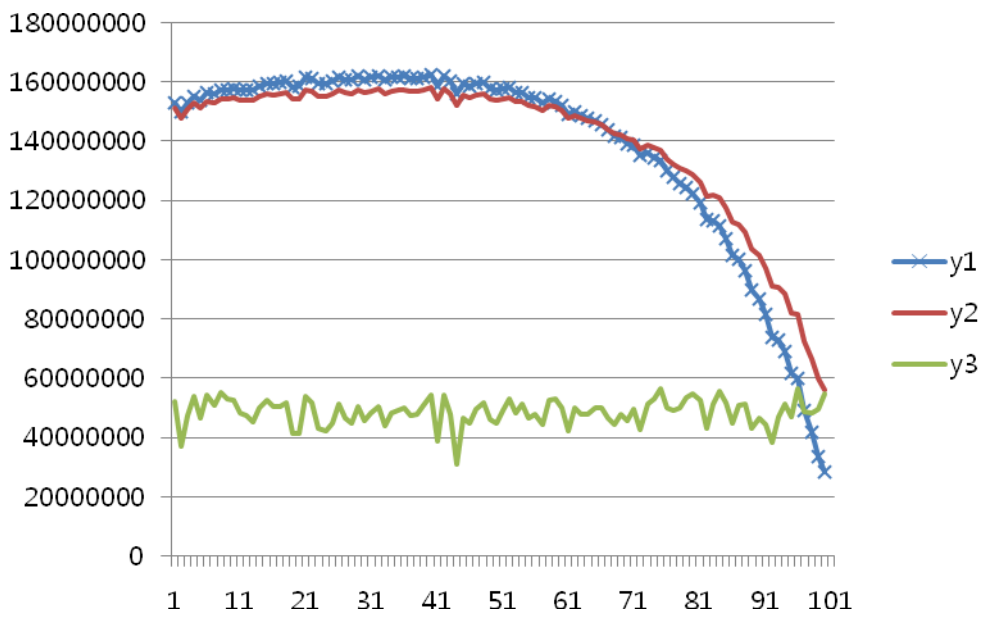

Figure 2.2: Optimal energy use pattern (unit: MWh)

Given the assumption that electricity from wind energy must be determined from outside our maximization model, optimal fossil fuel energy consumption is estimated by considering the carbon emissions damage cost to our society. Figure 2.2 summarizes the optimal energy use

patterns over 100 years. It is found that fossil fuel energy consumption decreases over time, because the GHG damage cost of traditional fossil fuels is considered in our model. The amount of electricity produced from coal is greater than that from natural gas in the initial period. After 70 years, the situation changes and energy consumption from natural gas becomes the primary source of elecricity in the society. It is explained that carbon emissions produced in the generation of electricity from natural gas is less than that of coal and the cost of carbon damage plays an important role over time when the utility maximization problem is solved.

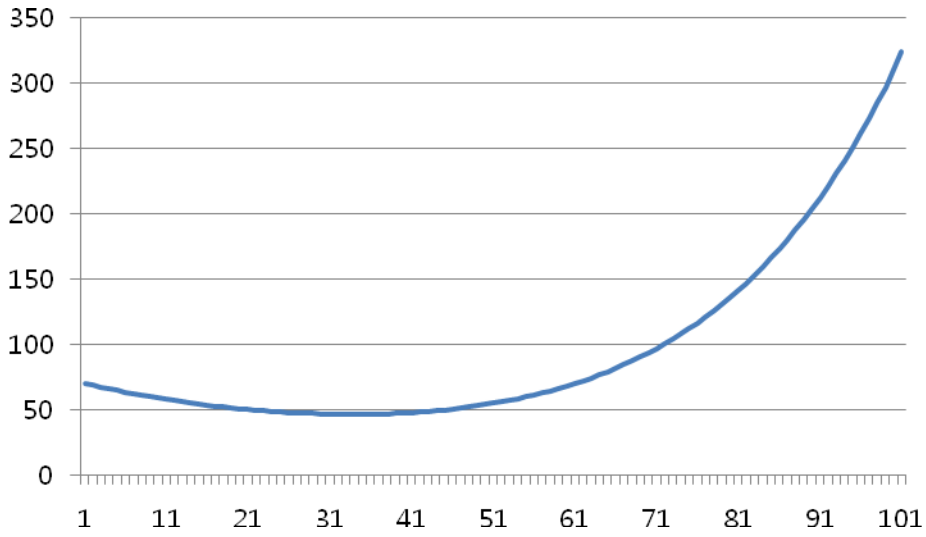

Figure 2.3: Carbon shadow price (unit:dollars)

Figure 2.3 is the plot for carbon shadow price over time. It is shown that carbon shadow price decreases slightly during the 1- to 40-year period and steadily increases after 40 years. In the initial period, the total fossil fuel consumption goes up due to the uncertainty of wind energy production; therefore, carbon shadow price goes down. On the other hand, the carbon shadow price dramatically increases over time after the initial 40-year period.

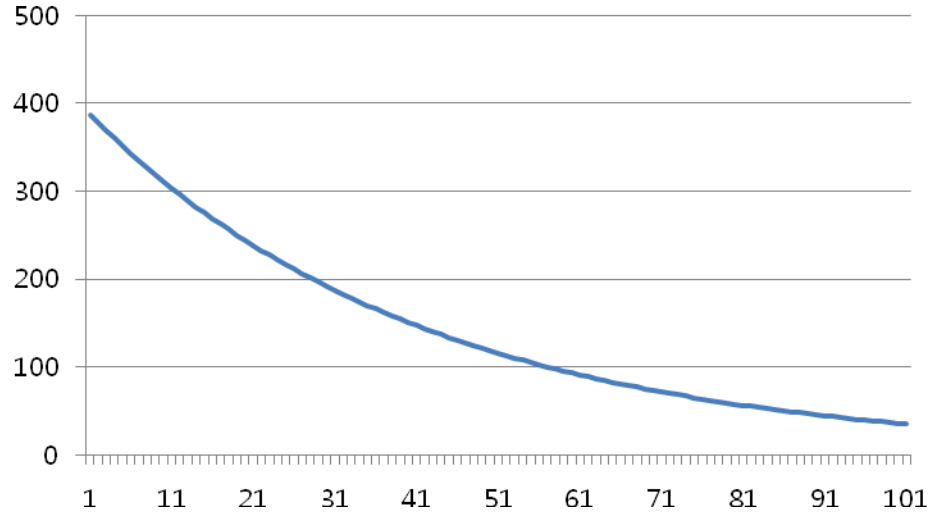

Figure 2.4: Carbon stock (unit: ppm)

Figure 2.4 summarizes the carbon stock in the air. In Chapter 2, only carbon emissions from the electricity sector are considered and other emission sources are ignored. In Figure 2.4, it is shown that carbon emission stock from electricity decreases over time and will stabilize after 100 years. Finally, using these results, the optimal carbon emission cap for RGGI is calculated. It is known that CO_2 stock is declinded as $C = C_0 e^{-\eta t}$. Using the last value of CO_2 stock from the simulation result, η is calculated as follows:

$$\eta = \frac{1}{100}\ln(\frac{387}{309.8692748}) = 0.000965324$$

Using this optimal carbon emission stock, the optimal carbon emission cap for RGGI is determined. If we set the carbon emission cap equal to the optimal carbon stock from our model, the emissions market will work efficiently and the carbon price from the emissions market will

equal the carbon shadow price, fully covering the carbon emission damage cost. To get the optimal results, we have to reduce initial carbon emissions cap as 80%.

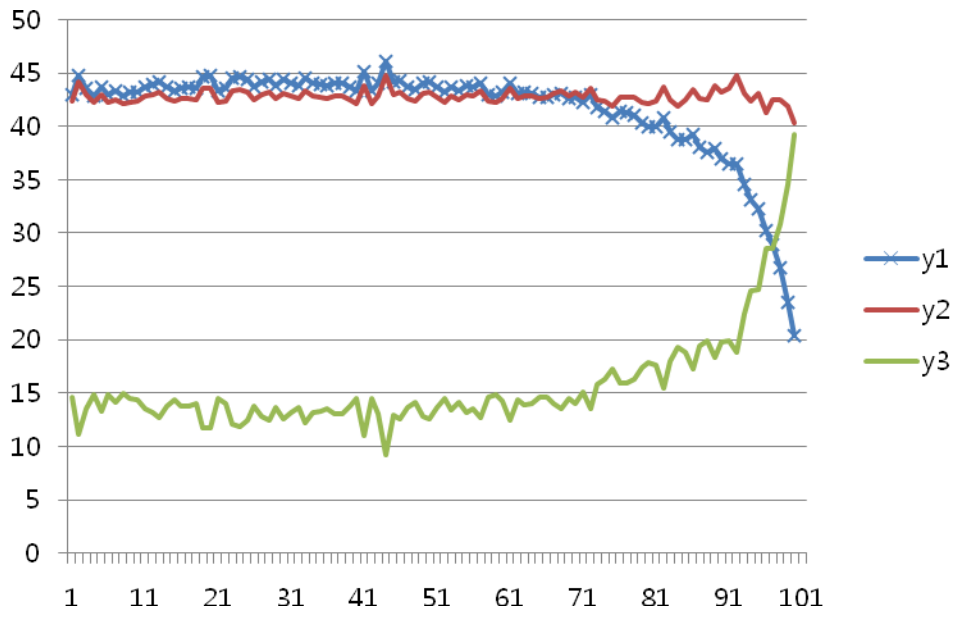

Figure 2.5: Optimal energy use portfolio (unit: %)

Ultimately, we arrive at an optimal energy use portfolio. If the social cost of carbon and uncertainty of wind energy generation are considered, an optimal energy use portfolio is derived over time. Electricity generation from coal decreases from 43% to 20% over time, On the other hand, the consumption proportion of renewable energy increases rapidly due to zero carbon emissions despite the uncertainty issue inherent in the production of wind energy. Meanwhile, electricity from natural gas is a stable commodity and maintains a 42% share in the national consumption picture.

2.3.2 Sensitivity analysis

A) Energy portfolio with increasing wind energy variability

Wind energy is not a stable source of electricity. As long as the wind blows, electricity from this clean energy source can be generated. When the wind stops, no energy can be produced. Therefore, the variability of wind energy is the main issue in any future energy portfolio plan. In our model, the variability of wind speed has a huge effect on fossil fuel energy consumption. If the wind speed variance is increased in our model, the electricity production from traditional fossil fuels shows huge volatility. Therefore, it is concluded that wind energy variability also affects traditional fossil fuel consumption over time.

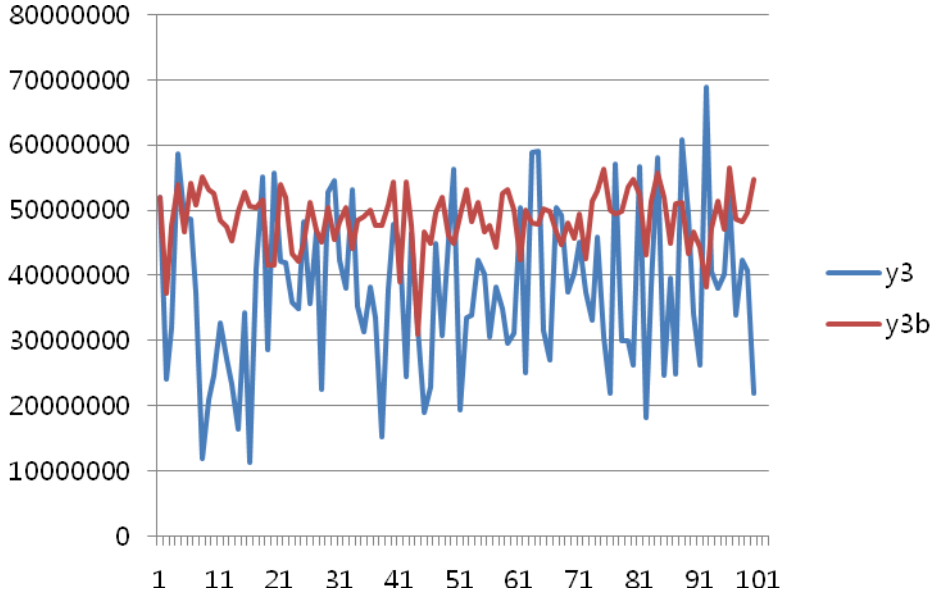

Figure 2.6: Wind energy: baseline case (y3b) and new case (y3) (unit: MWh)

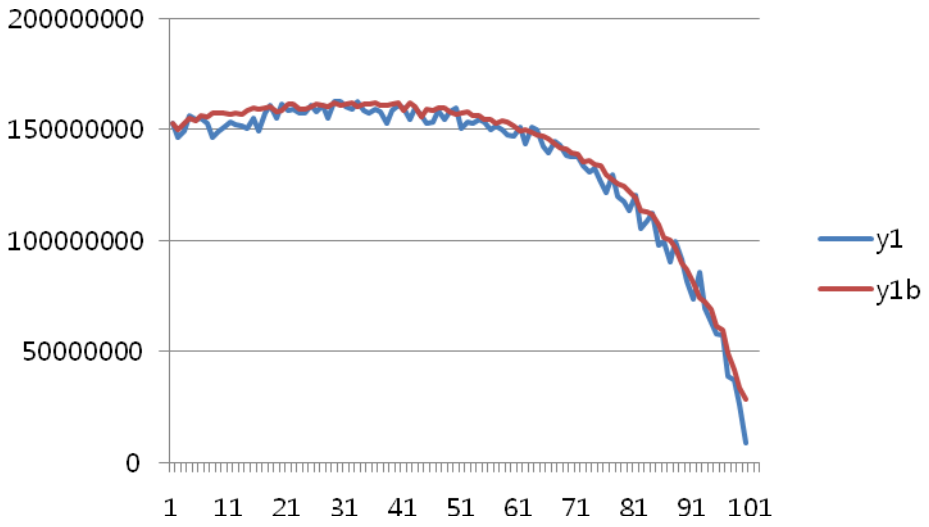

Figure 2.7: Electricity from coal: baseline case (y1b) and new case (y1) (unit: MWh)

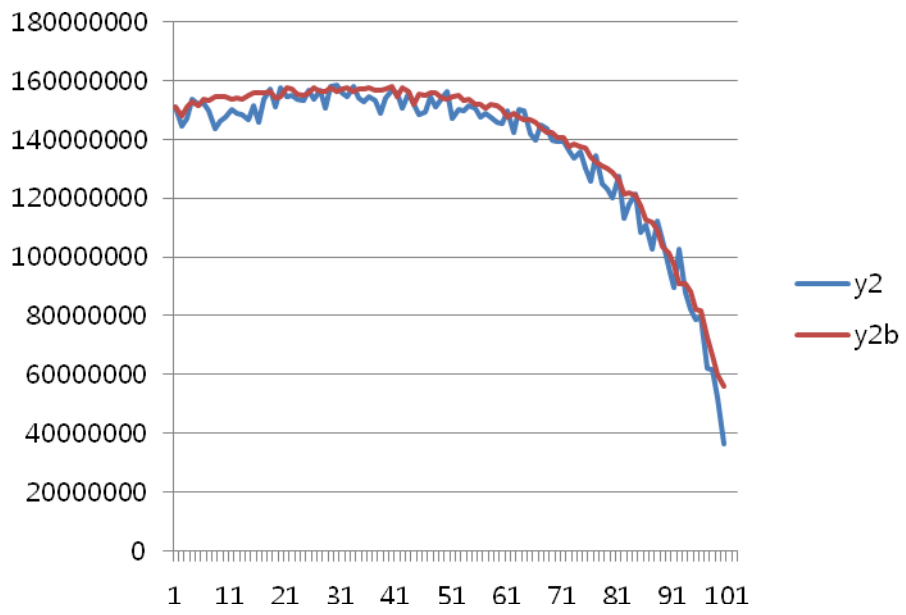

Figure 2.8: Electricity from natural gas: baseline case (y2b) and new case (y2) (unit: MWh)

B) Carbon damage cost parameter change

The carbon damage cost parameter "d" also plays a main role when social welfare is estimated and optimal energy use is calculated in our model. If a large number is used for carbon damage cost, traditional fossil fuels consumption is reduced and carbon emissions decrease. On the other hand, if a small value is selected for carbon damage, the damage from GHG is underestimated and power plants will continue to depend on coal and natural gas to generate electricity. As the carbon damage parameter "d" moves from 16 to 50, it is concluded that the carbon shadow price increases and the rate of increase escalates over time.

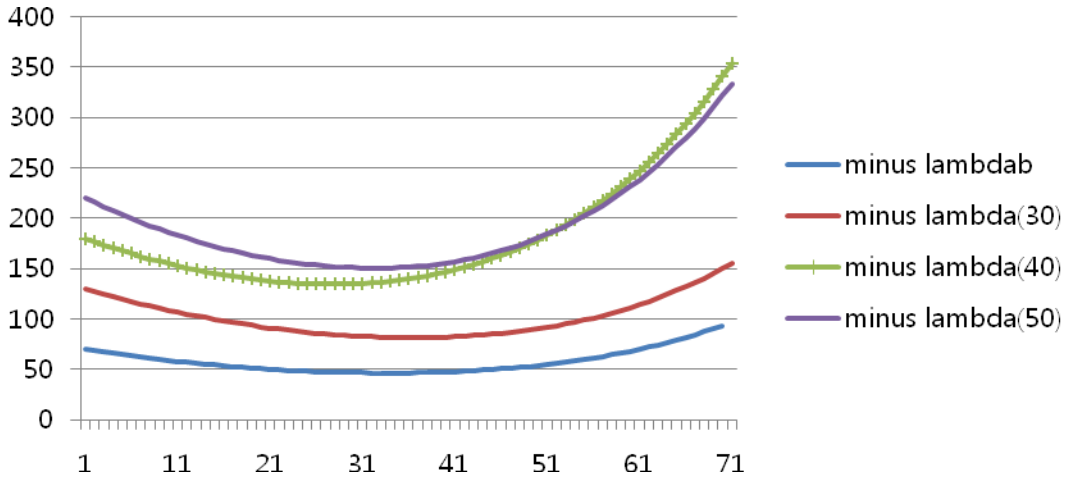

Figure 2.9: Carbon shadow price change (unit: dollars)

The changed carbon damage parameter also affects fossil fuel consumption. If the carbon damage cost increases, the electricity from coal and natural gas decreases, because traditional

fuels emit substantial carbon dioxide and the increased “d” parameter can amplify damage cost from these carbon emissions.

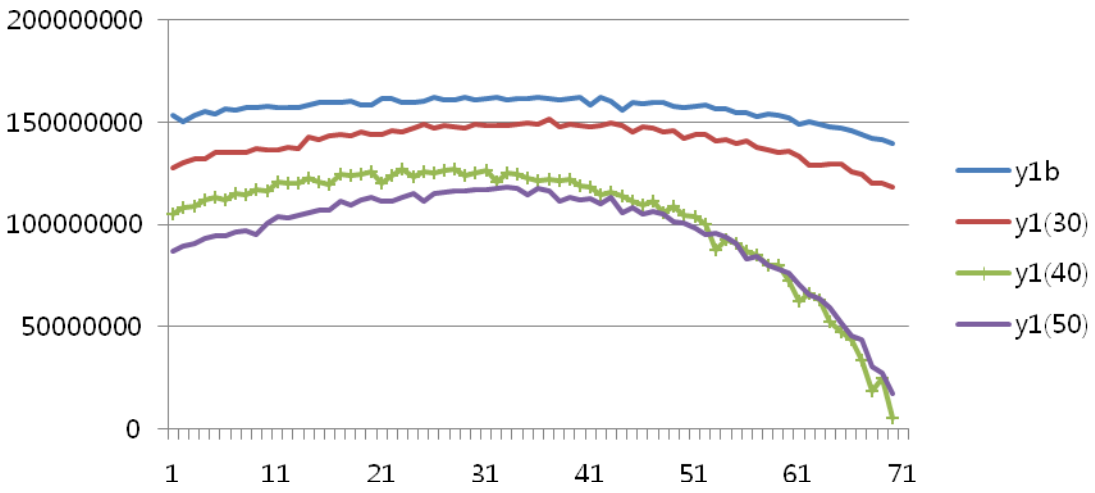

Figure 2.10: Electricity from coal: baseline case (y1b) and new cases (unit: MWh)

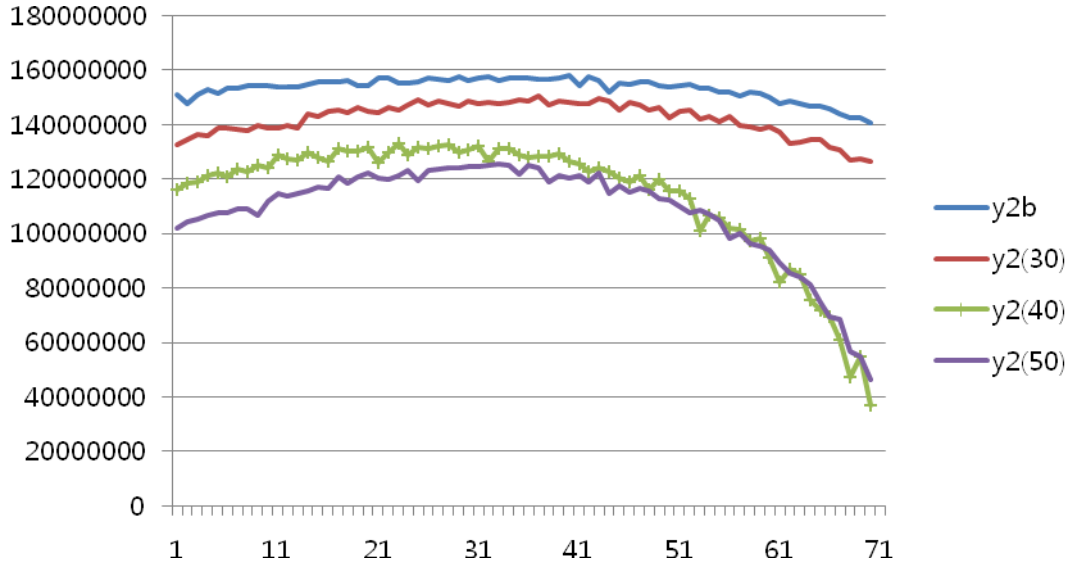

Figure 2.11: Electricity from natural gas: baseline case (y2b) and new cases (Unit: MWh)

C) Discount rate change

Discount rate is a controversial issue in the climate change arena. If a low number is used for a discount rate, future generation welfare and carbon damage cost are overestimated. On the other hand, if a high discount rate is selected for the economic model, the impact of carbon damage is underestimated and current fossil fuel consumption increases. Hence, it is necessary to analyze the impact of a changing discount rate in our social welfare maximization model.

First, if the discount rate is raised from 0.01 to 0.03, the carbon shadow price generally decreases. If we compare the baseline case (discount rate 0.02) with a second case (discount rate 0.03), the carbon shadow price in the latter case becomes much lower over time. In the initial period, the 0.01 discount rate case results in the highest carbon shadow price, but the rate of the price increase for this case slows after 30 years.

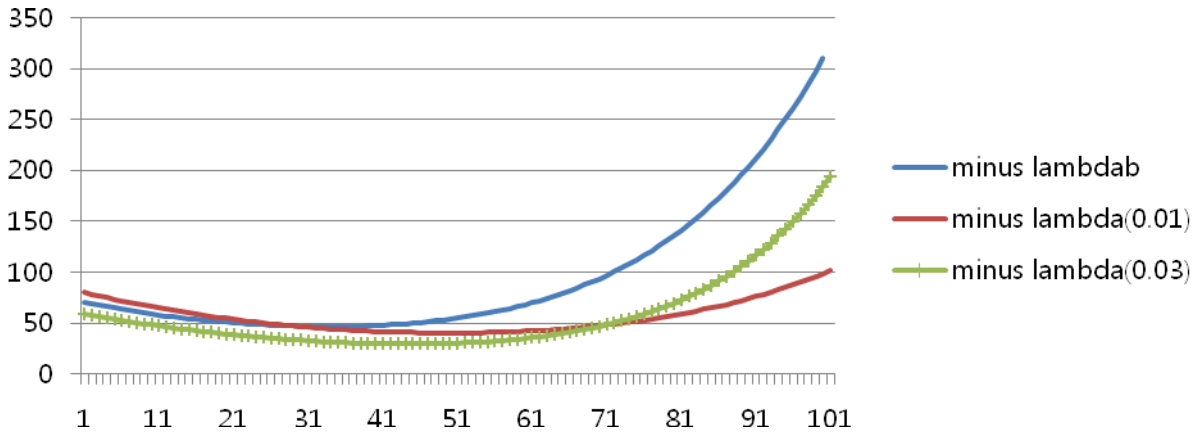

Figure 2.12: Carbon shadow price change (unit: dollars)

Second, it is necessary to consider fossil fuel consumption over time. As we expected, the electricity from fossil fuel sources increases when the discount rate is raised from 0.02 to 0.03. To conclude, the discount rate is related to the equity problem in balancing current and future generations' welfare and estimating damage cost from carbon emissions. Therefore, the rate affects the carbon shadow price and traditional energy use pattern over time.

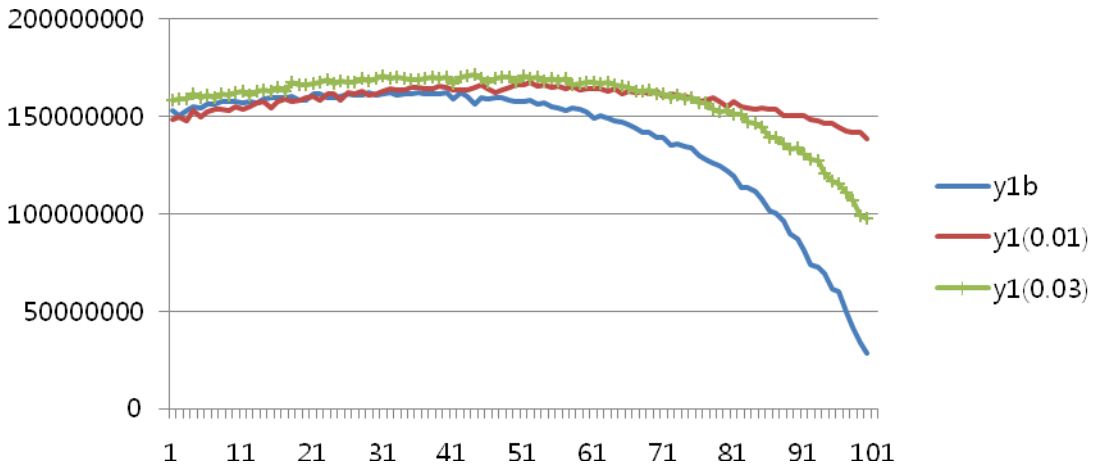

Figure 2.13: Electricity from coal: baseline case (y1b) and new cases (unit: MWh)

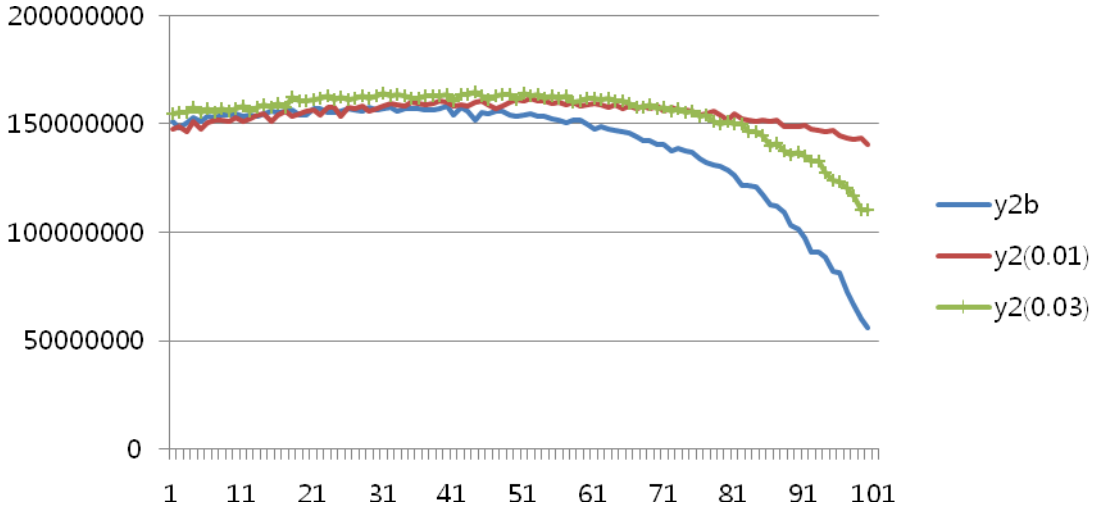

Figure 2.14: Electricity from natural gas: baseline case (y2b) and new cases (unit: MWh)

2.4 Conclusion

Decreasing carbon emissions is a major concern around the world. To reduce GHG and strike a balance between growing the economy and protecting the environment, sustainable development has entered the spotlight. Without carbon reduction by the electric utilities, we cannot achieve sustainability because the electric utilities are the biggest source of carbon emission. There are several approaches by which to reduce GHG from this source. One of them is the RGGI cap and trade system. The key to the success of this system is to set up an appropriate initial carbon emission cap and price for the carbon emissions market. To calculate the optimal carbon emission ceiling, price and fossil fuel energy use patterns, a utility maximization problem over time is developed and a nonlinear problem is solved using algorithm.

If carbon damage cost is introduced to our system, coal and natural gas consumption is reduced over time, because the GHG from traditional fossil fuels raise the carbon damage cost for each period and continue to increase dramatically over time. From the maximization problem, the appropriate carbon price is determined to be $60/tCO2e. Under the current carbon emission cap, the estimated current carbon emission price is just $2/tCO2e, which is far from the optimal result.

It is essential to conduct a sensitivity analysis considering several parameters such as wind speed variance, carbon emission marginal cost, and discount rate which all can play a major role in the decision making process of our model. Wind energy is not a reliably stable power source; electricity is generated only if the wind blows. It is concluded that wind speed variance affects

our utility maximization decision process. If the wind speed variance is increased, the variance of traditional energy consumption is also raised and total energy use is decreased because of wind energy uncertainty. Therefore, it is necessary to develop a reliable wind energy storage system to control the wind energy instability problem. The carbon emission cost parameter also affects results. If the value of GHG damage cost increases in our system, traditional fossil fuel consumption decreases, because the damage cost from carbon emissions is greater than the benefit from energy use. Lastly, discount rate can be important in our model. If the discount rate is increased, the future carbon emission damage cost is underestimated. Hence, electricity from coal and natural gas is greater than that of the base line case.

Optimal energy use patterns are also figured in. In the initial period, coal consumption is at its highest and accounts for 43% of total energy consumption. On the other hand, after 70 years, natural gas consumption is greater than any other energy source due to its low carbon emissions. Wind as a renewable source, increases over time from 14% to 40% over 100 years. The U.S. government intends to increase wind energy use to 20% by 2020. From the results in Chapter 2, it is concluded that implementation of a carbon emissions market is not enough to achieve this goal. In order to reach this ambitious target of 20%, it is essential to invest money to increase the number of wind farm facilities and wind energy storage systems.

There are some limitations in our model. First of all, except for electricity generation, other carbon emission sources are not covered in Chapter 2. If the other sources are introduced, the carbon concentration equation changes and the optimal results will change. Second, other emissions such as SO_x and NO_x are not included in the discussion of the electricity generation

process. Chapter 2 considers only one carbon emission, CO_2, in the damage cost. When damage costs of other emissions are introduced, the optimal results are affected.

Baseline case results

t	shadow price of carbon(dallars)	y1(MWh)	y2(MWh)	y3(MWh)	C (ppm)
0	70.000	1.53E+08	1.51E+08	52025000	387.000
1	68.595	1.5E+08	1.48E+08	37237634	377.742
2	67.235	1.53E+08	1.51E+08	47618827	368.706
3	65.921	1.55E+08	1.53E+08	53899340	359.887
4	64.652	1.54E+08	1.51E+08	46592077	351.281
5	63.426	1.56E+08	1.54E+08	54172627	342.880
6	62.245	1.56E+08	1.53E+08	50868169	334.682
7	61.107	1.57E+08	1.54E+08	55028051	326.681
8	60.011	1.57E+08	1.54E+08	53057284	318.871
9	58.959	1.58E+08	1.54E+08	52516970	311.249
10	57.949	1.57E+08	1.54E+08	48467288	303.811
11	56.980	1.57E+08	1.54E+08	47354305	296.550
12	56.054	1.57E+08	1.54E+08	45223288	289.464
13	55.170	1.59E+08	1.55E+08	49850776	282.548
14	54.327	1.6E+08	1.56E+08	52785480	275.798
15	53.526	1.59E+08	1.56E+08	50536746	269.210
16	52.766	1.6E+08	1.56E+08	50460617	262.780
17	52.048	1.6E+08	1.56E+08	51542989	256.505
18	51.371	1.58E+08	1.54E+08	41558558	250.380
19	50.736	1.58E+08	1.54E+08	41576576	244.402
20	50.143	1.62E+08	1.57E+08	53965495	238.568
21	49.592	1.61E+08	1.57E+08	51923337	232.874
22	49.083	1.59E+08	1.55E+08	43259241	227.317
23	48.617	1.59E+08	1.55E+08	42219837	221.893
24	48.194	1.6E+08	1.56E+08	44829790	216.599
25	47.814	1.62E+08	1.57E+08	51149064	211.432
26	47.477	1.61E+08	1.56E+08	46758379	206.389
27	47.185	1.61E+08	1.56E+08	45053145	201.467
28	46.938	1.62E+08	1.57E+08	50469045	196.664
29	46.736	1.61E+08	1.56E+08	45532414	191.976
30	46.581	1.61E+08	1.57E+08	48137871	187.400
31	46.472	1.62E+08	1.58E+08	50426267	182.934
32	46.411	1.61E+08	1.56E+08	44026774	178.575
33	46.399	1.62E+08	1.57E+08	48342969	174.321

34	46.436	1.62E+08	1.57E+08	49105176	170.169
35	46.524	1.62E+08	1.57E+08	50040460	166.117
36	46.663	1.61E+08	1.57E+08	47641248	162.162
37	46.855	1.61E+08	1.57E+08	47664386	158.302
38	47.102	1.62E+08	1.57E+08	50741801	154.534
39	47.404	1.62E+08	1.58E+08	54424285	150.857
40	47.763	1.59E+08	1.54E+08	38962772	147.269
41	48.181	1.62E+08	1.58E+08	54257184	143.765
42	48.658	1.6E+08	1.56E+08	47714847	140.347
43	49.197	1.56E+08	1.52E+08	31027145	137.010
44	49.800	1.59E+08	1.55E+08	46679794	133.752
45	50.469	1.59E+08	1.55E+08	44863937	130.574
46	51.205	1.59E+08	1.56E+08	49625843	127.471
47	52.011	1.6E+08	1.56E+08	51941586	124.443
48	52.889	1.58E+08	1.54E+08	46034975	121.488
49	53.841	1.57E+08	1.54E+08	44851518	118.604
50	54.871	1.58E+08	1.54E+08	49280985	115.788
51	55.979	1.58E+08	1.55E+08	53145219	113.040
52	57.171	1.56E+08	1.53E+08	48220864	110.358
53	58.447	1.57E+08	1.54E+08	51134650	107.741
54	59.812	1.55E+08	1.52E+08	46578149	105.186
55	61.268	1.54E+08	1.52E+08	47723643	102.692
56	62.820	1.53E+08	1.5E+08	44203548	100.258
57	64.470	1.54E+08	1.52E+08	52647439	97.882
58	66.222	1.54E+08	1.52E+08	53221769	95.563
59	68.081	1.52E+08	1.5E+08	50057727	93.300
60	70.050	1.49E+08	1.48E+08	42298896	91.091
61	72.134	1.5E+08	1.49E+08	49950066	88.934
62	74.338	1.49E+08	1.48E+08	47977046	86.829
63	76.665	1.48E+08	1.47E+08	47934364	84.775
64	79.122	1.47E+08	1.47E+08	50229684	82.770
65	81.713	1.46E+08	1.46E+08	49815350	80.812
66	84.444	1.44E+08	1.44E+08	46672827	78.902
67	87.320	1.42E+08	1.42E+08	44620932	77.037
68	90.348	1.41E+08	1.42E+08	48030067	75.216
69	93.534	1.39E+08	1.41E+08	45646643	73.439
70	96.885	1.39E+08	1.4E+08	49502818	71.704
71	100.407	1.35E+08	1.38E+08	42564944	70.011

72	104.107	1.36E+08	1.39E+08	51438098	68.358
73	107.994	1.35E+08	1.38E+08	52908386	66.744
74	112.076	1.34E+08	1.37E+08	56313828	65.170
75	116.359	1.3E+08	1.34E+08	50086245	63.632
76	120.854	1.28E+08	1.32E+08	49351731	62.131
77	125.569	1.26E+08	1.31E+08	49815623	60.666
78	130.514	1.24E+08	1.3E+08	53535690	59.235
79	135.699	1.22E+08	1.29E+08	54670353	57.839
80	141.134	1.19E+08	1.26E+08	52458118	56.475
81	146.830	1.14E+08	1.21E+08	43156743	55.144
82	152.798	1.13E+08	1.22E+08	51338002	53.844
83	159.051	1.12E+08	1.21E+08	55799320	52.575
84	165.600	1.07E+08	1.17E+08	51962919	51.336
85	172.460	1.02E+08	1.13E+08	44861076	50.126
86	179.642	1E+08	1.12E+08	50940745	48.944
87	187.163	96477502	1.09E+08	51155603	47.790
88	195.036	89750673	1.04E+08	43246974	46.663
89	203.277	86753487	1.02E+08	46595657	45.562
90	211.902	81428565	97240248	44379599	44.487
91	220.929	73995678	90922485	38138989	43.437
92	230.375	72731283	90796407	47193060	42.410
93	240.259	69130080	88396157	51333654	41.408
94	250.601	61502962	82042349	47097489	40.430
95	261.420	59766631	81610734	56494347	39.473
96	272.738	49378292	72624695	48719454	38.539
97	284.577	41763699	66462659	48230215	37.626
98	296.961	33745675	59964129	49569277	36.733
99	309.913	28357370	56151900	54689819	35.860

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CHAPTER 3

THE EFFECT OF CONTROLLABLE ELECTRICITY DEMAND ON DAILY LOAD AND PRICE PRFILES

3.1 Introduction

A Smart Grid is a two-way communication system that allows for communication between the electrical utility and its customers, and the sensing of power flows along the transmission lines. This technology will work with the electrical grid to respond to quickly changing electric demand. Under the smart grid, controllable load is a major component, enabling customers to respond to market signals provided by electricity suppliers to lower energy costs and increase system reliability. The advantages of controllable load are significant. First, it lowers average electricity price by trimming expensive peak load. This allows electricity suppliers to reduce the use of more costly generators and eventually save the capacity cost of building new power plants as the system that supplies peak-demand needs is shifted to off-peak hours. The controllable load concept also makes it easier to accommodate non-dispatchable renewable energy. In the case of wind energy, wind blows more at night than during the day. Therefore, increasing new night electricity demand by using controllable demand like thermal storage can be a good option to mitigate the variability of electricity production from renewable sources.

Thermal storage, used mainly for cooling purposes, is one type of controllable load which has great potential for wide-spread use due to its significant and imminent cost-saving effect and its potential to replace traditional air conditioners with reasonable installation cost and minimal

customer discomfort. Air conditioning of private residences and commercial buildings during summer days is the main cause of peak power demand. In addition to the original load needed for lighting, computers, operational equipment, etc., the demand for electricity dramatically increases on summer afternoons as people crank up the air conditioners to maintain more comfortable indoor temperatures. Although it was shown in Chapter 1 that PHEV can contribute to the flattening of electricity load and price, their effect is relatively small. It is therefore necessary to explore another, more effective method to stabilize the daily electricity load -- thermal storage.

In the case of New York City, peak and off-peak demand during the August of 2008 was approximately 11000 MWh and 7500 MWh, whereas the peak demand in winter was only 7500 MWh. This clearly indicates that a larger amount of electricity is used for cooling than for heating. Furthermore, within a given day, the large load difference between peak hour and off-peak hour increases the benefit of thermal storage even further by taking advantage of off-peak prices. In addition to the cost-saving effect for customers, electricity suppliers can also save potential capacity cost of building new power plants.

From the NERC 2010 Long-Term Reliability Assessment report, it is known that most industries forecast electricity load annually. This forecast is based on annual forecast growth rate[12] and normal weather. The problem with this kind of load forecasting is that the electricity

[12] The forecast growth rates are average annual rates calculated for the weather-normalized projections from the first year to the last year of the forecast period (source: 2010 Long-Term Reliability Assessment October 2010).

load is exogenous and cannot respond to price. This model also cannot make a distinction between temperature-sensitive load (TSL) and non-temperature-sensitive load (N-TSL) as part of total electricity load. To introduce demand response and test the benefit of thermal storage, it is essential to develop a new load estimation model which can divide load into N-TSL and TSL, which is the only load that could be affected by thermal storage.

Peak load is categorized as either N-TSL or TSL. N-TSL is any basic electricity demand not affected by temperature such as that required for lighting and home appliances. On the other hand, TSL is affected by temperature. Air conditioning demand is the key source of TSL during the summer months. Electricity load has a huge volatility and can result in hefty social costs and so flattening electricity load and price is essential in the electricity industry. Chapter 3 of this paper is the first attempt to divide the total electricity load into TSL and N-TSL using econometric modeling.

Here in Chapter 3 are suggestions for econometric models which estimate hourly electricity demand sensitive to temperature, and measure the proportion of TSL and N-TSL and the electricity price associated with each. Using these estimated models to capture the dynamics of electricity price and the two types of loads, this paper investigates the associated optimal scheduling of electricity demand controlled by thermal storage facilities in New York and New England.

If we can determine the exact amount of TSL in the summer, we can use this result to determine how to flatten traditional electricity load and price using thermal storage, in particular

through the use of ice. These days thermal storage has come into the lime light as an efficient substitute for the cooling components in air conditioning systems in buildings and homes. When electricity price is low at night, electricity is kept in storage as ice. The ice is then melted to cool the air during the day. If an air conditioner cooling system is replaced with ice, the traditional load is flattened and power plants' construction costs are reduced. Since only TSL is controllable using an ice battery, we attempt to arrive at our energy cost minimization model by showing how summer TSL electricity costs can be controlled using an ice-based thermal storage system.

The data and model for electricity load and price in summer and winter are discussed in section 3.3. Section 3.4 shows the energy cost minimization results from section 3.3 using an ice battery and TSL during summer months. Section 3.5 summarizes the conclusion.

3.2 Literature review for load forecasting and demand response with storage

The demand response concept started in the 1970s with direct load control programs and tariffs. At that time, increasing demand for air conditioning sparked interest in managing electricity load. By the late 1970s and 1980s, utility companies recognized the system cost impact of meeting peak loads and began to view load management as a reliability resource.

In the mid-1990s, policymakers were interested in the development of regional, competitive electricity markets and initially focused on market design and structure. However, these ventures were not completely successful and attention turned to the more practical premise that demand response is essential to the efficient functioning of wholesale electric markets. The Energy Policy

Act (EPACT) of 2005 played a major role in eliminating unnecessary barriers to wholesale market participation by demand response in the energy, capacity, and ancillary service markets.

There are three general ways in which demand response is carried out. First, customers can reduce their electricity usage during specific peak periods without changing usage behavior during other periods. For instance, customers turn off air conditioners or heaters at peak times to save on their electricity bills. Second, customers can change their electricity consumption patterns by shifting some of their electricity usage to off-peak periods. For example, they do laundry at night when the electricity price is cheap. Lastly, there is voluntary behavioral response. Customers reduce their demand for electricity at peak periods when prices are higher to benefit economically. In this chapter, we look more closely at the third demand response as it relates to thermal storage.

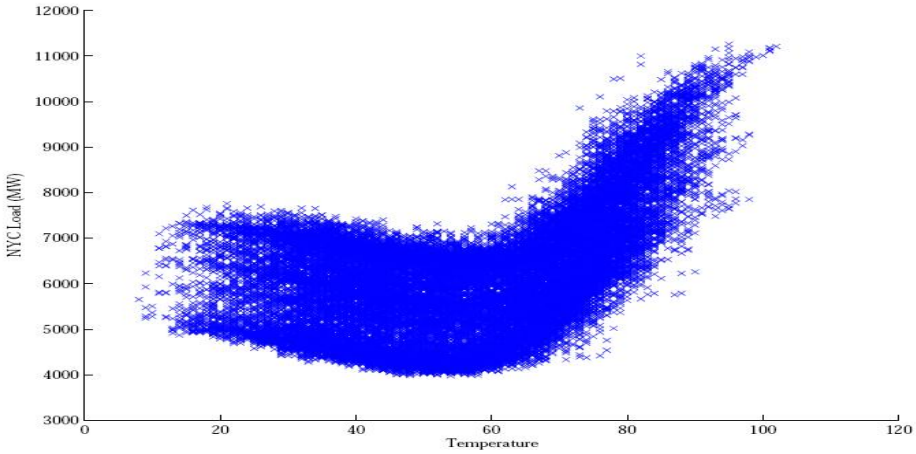

Figure 3.1: Relationship between temperature and NYC load (from 2008 to 2010)

The scatter plot in Figure 3.1 clearly shows that temperature is the main factor influencing electricity load. The load grows during lower winter temperatures as well as during higher summer temperatures. But the load response to temperature is different. In summer, the load is more sensitive to temperature than in winter. From Figure 3.1, we see that temperature is the most important factor affecting electricity load during the summer and that it is important to distinguish the temperature impact on TSL and N-TSL. However, current and past research on the estimation and forecast of electricity load has not dealt with these temperature effects and distinctions thoroughly enough.

There is a good body of research which focuses on electric load forecasting and the impact of weather. Fan and McDonald (1994) presented a real-time implementation of short-term load forecasting using an autoregressive moving-average (ARMA) model. Hyde and Hodnett (1997) presented a weather load model to predict demand for the Irish electricity supply system. To include weather impact, the model was developed using a regression analysis of historical load and weather data. Alfares and Nazeeruddin (1999) presented a regression based on a daily peak-load forecasting method which spanned an entire 365-day year. In order to forecast load in their model, different climatic factors from season to season were considered. Juberias et al (1999) developed a real-time load forecasting autoregressive integrated moving-average (ARIMA) model including meteorological influences. However none of this previous research distinguishes TSL and N-TSL in their discussion of demand response. In terms of voluntary consumer demand response, it is essential to find out how much electricity could be contained in thermal energy storage systems.

3.3 Electricity load and price Model using Two Stage Least Squares (TSLS) Method

Electricity load and price models were estimated in Chapter 1 to find the effect of PHEVs on an electricity market. In Chapter 3, we also want to estimate hourly electricity load and distinguish TSL from N-TSL using a different estimation model from that in Chapter 1. In this chapter, it is assumed that load and price are determined simultaneously, so to estimate electricity load and price in summer and winter, the Two Stage Least Squares (TSLS) method is utilized. Even though the structure of the price and load equations is still recursive (Load affects price but price does not affect load), the residuals of the two equations are found to be correlated with each other and the statistical model is not strictly recursive. Here it is also assumed that electricity load and price equations are dynamic and are affected by distributed lags of electricity loads and prices. To include this specification, we add lagged loads and prices as explanatory variables in the final estimation model.

In step1 of this method, reduced forms are used to estimate predicted values of electricity load and price with the same set of all explanatory variables in each equation together with all lagged prices and loads. In step 2, the final structural forms for load and price are estimated using the predicted values of the current load and price from step 1 as regressors. Separate models are estimated for the summer and winter periods.

Although the predicted current load is an important explanatory variable in the price equation, the current price is not an important explanatory variable in the load equation and most estimated coefficients have perverse signs. As a final check, a Granger causality test is executed

for testing whether lagged prices “cause” load. The Granger causality test shows that load is not affected by lagged prices Even though price is not part of the structure. In electricity markets, most consumers don’t react to real time prices now because they get their electricity bills using a fixed price regime. Therefore, it is reasonable that price doesn’t explain load behavior and the predicted value of current price is not one of the explanatory variables in the final electricity load model. However, demand response is becoming more important and a real time pricing regime will be realized more widely under a smart grid system. Therefore, it is highly likely that a simultaneous estimation model will be needed to estimate electricity load and price in the future.

Hourly electricity load and price data have a strong time-series character which results in autocorrelation among residuals over time. To remedy this, AUTOREG is implemented. Coupling a regression model with an autoregressive model allows for the random error to correct for the autocorrelation of the errors. The basic AUTOREG model is below.

$$
\begin{aligned}
&y_t = x_t^{'}\beta + v_t \\
&v_t = -\varphi_1 v_{t-1} - \varphi_2 v_{t-2} - \cdots - \varphi_m v_{t-m} + \varepsilon_t \\
&\varepsilon_t \sim IN(0, \sigma^2)
\end{aligned}
$$

The primary purpose of Chapter 3 is to estimate electricity load and price in summer and winter, and separate TSL and N-TSL from the load estimation. For this reason, the dependent variables are specified in the natural units in an additive model and not converted to logarithms in a multiplicative model as they are in Chapter 1. N-TSL is defined as intercept, lagged electricity loads, and seasonal cycles in the load model and TSL is defined as temperature-related

terms only in load estimation. Therefore, TSL and N-TSL are separated from the final load estimation model as below.

$$Summer\ load = \underbrace{\alpha + \beta_i * seosonal\ cycles + \delta_i * lagged\ summer\ loads}_{\text{N-TSL}}$$
$$\underbrace{+\gamma_1 * CDD + \gamma_2 * CDD^2 + \phi_i * Cross\ product\ among\ CDD\ \&\ cycles}_{\text{TSL}} + \varepsilon$$

$$Winter\ load = \underbrace{\alpha + \beta_i * seosonal\ cycles + \delta_i * lagged\ winter\ loads}_{\text{N-TSL}}$$
$$\underbrace{+\gamma_1 * HDD + \gamma_2 * HDD^2 + \phi_i * Cross\ product\ among\ HDD\ \&\ cycles}_{\text{TSL}} + \varepsilon$$

To capture temperature sensitivity in the summer load model, CDD (CDD = max (temperature – 65, 0)) and squared CDD are used since the load rises dramatically when temperatures reach 65℉ and above. To model the winter temperature sensitive load, a new hdd and squared new hdd are used. The new hdd is defined as below.

New hdd=max (40-temperature, 0)

Normally, electricity demand for heating is not sensitive from 40℉ to 65℉, and it is reasonable to use the new hdd to capture the winter load response to cold temperatures.

The short term volatility of electricity loads is driven by temperature, season, and time of day. To capture this seasonality in our model, several sine and cosine curves which capture weekly and daily patterns are made. In chapter 1, year and half-year sine and cosine curves are included to model yearly cycles in load and price. However, here in chapter 3 the yearly patterns are excluded. The purpose of chapter 3 is to divide load into temperature sensitive and non-temperature sensitive. If yearly cycles are added to the model, the impact of temperature is underestimated because temperature itself also has strong yearly cycles.

To estimate winter load and price, 6- and 12-hour cycles are included along with weekly and daily cycles. As we know, the shape of the winter load and price model is quite different from that of summer. Due to a second wave of heating demand at night, the winter load and price curve shows two humps. To reflect this specific characteristic, 6-hour and 12-hour daily cycles are added to the winter model.

As in Chapter 1, natural gas price is an important factor affecting electricity price. Chapter 3 uses Lagrange interpolation polynomials to generate weighted natural gas prices as shown below.

Where, $w_{31i} = \dfrac{(i-168)(i-336)}{(0-168)(0-336)}$

$$w_{32i} = \frac{(i-0)(i-336)}{(168-0)(168-336)}$$

$$w_{33i} = \frac{(i-0)(i-168)}{(336-0)(336-168)}$$

Finally, using these three weighted sums, three weighted natural gas prices are calculated. These sums serve as a weight when we calculate the weighted natural gas prices as follows:

$$wp_{kt} = \sum_{i=0}^{336} w_{ki} PNG_{t-i}$$

Lastly, we must capture the weekend effect which may be done in two ways: 1) A dummy variable is generated to indicate a weekend which simply changes intercept in our model; 2) a weekend cycle is generated. It is one (1) during weekdays and defined as a cosine cycle during the weekend. The second method not only changes intercept but also captures the nonlinear effect during weekends. In chapter 3, second method is chosen to capture the weekend effect.

To summarize, summer electricity load is a function of a time trend, lagged summer electricity loads (1, 24, and 25 lags), temperature, weekly cycle, daily cycle, weekend cycle, and cross effect among temperature and patterns.

In the summer price model, time trend, lagged summer electricity prices (1, 24, 25 lags), lagged summer electricity loads (1, 24, 25 hour lags) weekly cycle, daily cycle, weekend cycle, and natural gas prices can explain summer electricity prices. For winter load and price estimation, the basic models are identical to that of summer, except that 6- and 12-hour cycles are added.

Because this analysis deals particularly with the integration of Northeastern U.S. wind energy into the NPCC network, Chapter 3 identifies six regions for the purposes of our study:

NE1, NE2, Boston, NY1, NY2, and NYC. Specifically they refer to the following geographical areas:

NE1= Northern New England (Maine, New Hampshire, and Vermont).

NE2 = Southern New England (Connecticut, Rhode Island, and Massachusetts minus the Boston area).

Boston = Boston metropolitan area not included in NE2

NY1 = Western NY State (A, B, C, D, and E from the New York control area load zones map).

NY2 = Eastern NY State (F, G, H, I, and K E from the New York control area load zones map).

NYC = New York City metropolitan area not included in NY1 or NY2

New Hampshire and Connecticut temperatures are used as the representative temperatures in NE1 and NE2. Rochester and Albany temperatures are used as the representative temperatures in NY1 and NY2

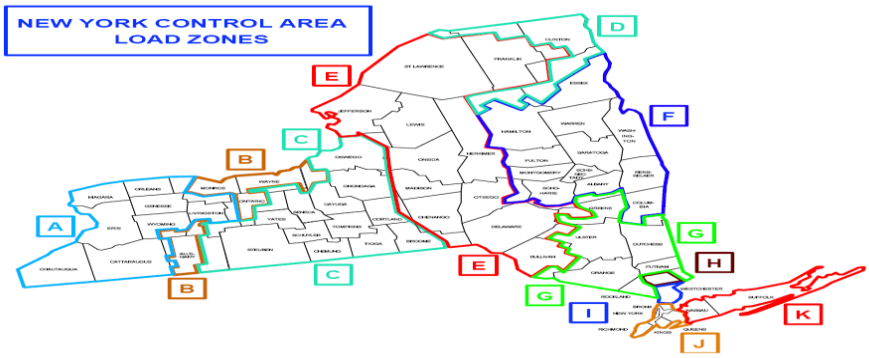

Figure 3.2: New York control area load zones (source: NY ISO web site)

Table 3.1: Summer hourly data: basic statistics[13]

(April to September, 2007, 2008, 2009, and 2010)

variables	mean	min	max	std Dev
NE1 summer load (MWh)	3270.79	2052.00	5268.00	630.44
NE1 summer electricity price (dollars)	58.36	0.80	542.39	32.60
NE1 temperature (F)	61.69	18.00	98.00	13.40
NE2 summer load (MWh)	8507.11	4937.00	16047.00	2011.93
NE2 summer electricity price (dollars)	61.38	0.85	493.21	35.29
NE2 temperature (F)	65.43	24.00	101.00	12.54
Boston summer load (MWh)	3010.76	1891.00	5436.00	653.72
Boston summer electricity price (dollars)	59.61	0.84	544.68	34.66
Boston temperature (F)	64.81	28.00	99.00	11.72
NY1 summer load (MWh)	6254.59	4016.40	9806.40	1032.34
NY1 summer electricity price (dollars)	49.13	9.30	188.03	21.79
NY1 temperature (F)	62.96	20.00	95.00	12.43
NY2 summer load (MWh)	6372.66	3644.00	12756.10	1613.09
NY2 summer electricity price (dollars)	68.31	10.53	325.97	35.87
NY2 temperature (F)	63.93	21.00	96.00	12.20
NYC summer load (MWh)	6609.28	3982.50	11261.60	1462.32
NYC summer electricity price (dollars)	71.56	10.61	373.61	39.90
NYC temperature (F)	69.40	32.00	102.00	11.57
Natural gas price (dollars)	6.17	0.54	13.32	2.83

Table 3.2: Winter hourly data: Basic statistics

(October to March, 2007, 2008, 2009, and 2010)

variables	mean	min	max	std Dev
NE1 winter load (MWh)	3357.70	1949.00	4847.00	544.36
NE1 winter electricity price (dollars)	58.12	1.16	292.43	25.59
NE1 temperature (F)	32.53	-22.00	85.00	14.26
NE2 winter load (MWh)	8336.11	5023.00	12460.00	1430.84
NE2 winter electricity price (dollars)	60.35	1.20	299.71	26.88
NE2 temperature (F)	37.23	-2.00	89.00	13.55
Boston winter load (MWh)	2945.32	1909.00	4311.00	463.58
Boston winter electricity price (dollars)	58.89	1.19	290.36	26.08
Boston temperature (F)	39.05	3.00	85.00	12.57
NY1 winter load (MWh)	6477.82	4226.20	8897.70	972.21
NY1 winter electricity price (dollars)	49.76	12.47	184.69	18.99
NY1 temperature (F)	34.82	-4.00	83.00	13.60
NY2 winter load (MWh)	5799.66	3726.90	9014.80	1025.48

[13] We exclude zero variables of load and price data(black out case and starting or finishing daylight saving)

NY2 winter electricity price (dollars)	66.71	15.12	231.39	27.18
NY2 temperature (F)	34.39	-7.00	13.79	83.00
NYC winter load (MWh)	5800.02	3978.10	8866.60	956.72
NYC winter electricity price (dollars)	66.23	15.20	210.35	27.51
NYC tem (F)	42.99	8.00	88.00	12.57
Natural gas price(dollars)	5.85	2.31	9.89	1.71

3.*3.1 Estimating reduced form*

To arrive at a predicted value of electricity load and price, it is necessary in step 1 to estimate load and price as a function of seasonal cycles, lagged loads and prices, temperature, weekly cycles, and weighted natural gas prices together with residual structures which capture the correlation among 24 lagged residuals. After these equations are estimated, we arrive at the predicted value of electricity load and price and use them as the endogenous variables in step 2. Load and price for all six regions are estimated. The results for all regions except NYC are summarized in Appendix A.

Table 3.3: Summer load estimation results from step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	305.233	20.360	lag 1	-0.155	20.770
trend	0.000	0.840	lag 2	-0.204	-27.570
nycload1	0.871	233.890	lag 3	-0.034	-4.540
nycload24	0.521	79.830	lag 4	0.043	5.690
nycload25	-0.465	-69.430	lag 5	0.037	4.960
pnyc1	1.750	13.420	lag 6	0.034	4.530
pnyc24	1.890	12.120	lag 7	0.043	5.670
pnyc25	-3.063	-17.090	lag 8	0.030	4.040
c_24hour	-136.710	-35.220	lag 9	-0.010	-1.350

s_24hour	5.106	1.240	lag 10	-0.041	-5.400
c_week	16.329	5.630	lag 11	-0.002	-0.300
s_week	11.129	3.710	lag 12	0.034	4.560
weekend cycle	100.732	12.000	lag 13	0.017	2.250
cddc_24hour	-0.148	-0.460	lag 14	-0.002	-0.280
cdds_24hour	2.365	6.660	lag 15	0.024	3.130
cddc_week	0.195	0.690	lag 16	0.062	8.230
cdds_week	0.573	1.870	lag 17	0.061	8.090
cddweekendcycle	-0.537	-0.660	lag 18	0.020	2.640
cdd	11.387	12.820	lag 19	0.013	1.760
sq_cdd	-0.008	-0.310	lag 20	0.043	5.660
wp31	0.076	2.310	lag 21	0.039	5.130
wp32	-0.081	-3.080	lag 22	-0.041	-5.470
			lag 23	-0.196	-26.570
			lag24	0.177	23.850
	Adj R-Sq 0.991				

Table 3.4: Summer price estimation results from step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-0.603	-1.280	lag 1	-0.103	-13.670
trend	0.000	2.100	lag 2	-0.041	-5.500
nycload1	0.001	8.770	lag 3	0.000	0.010
nycload24	0.003	13.520	lag 4	0.033	4.440
nycload25	-0.004	-17.520	lag 5	0.024	3.250
pnyc1	0.853	204.260	lag 6	0.038	5.020
pnyc24	0.612	100.380	lag 7	0.026	3.440
pnyc25	-0.507	-76.010	lag 8	-0.015	-1.980
c_24hour	-0.968	-7.570	lag 9	-0.002	-0.260
s_24hour	-0.357	-2.720	lag 10	-0.006	-0.750
c_week	0.236	2.640	lag 11	0.033	4.440
s_week	-0.099	-1.070	lag 12	0.036	4.750
weekend cycle	0.556	2.280	lag 13	0.040	5.280
cddc_24hour	-0.099	-9.750	lag 14	0.010	1.390
cdds_24hour	0.003	0.290	lag 15	0.031	4.110
cddc_week	-0.008	-0.940	lag 16	0.030	4.030
cdds_week	0.013	1.340	lag 17	-0.003	-0.390
cddweekendcycle	0.006	0.230	lag 18	0.020	2.710
cdd	-0.083	-3.030	lag 19	0.021	2.840
sq_cdd	0.006	8.210	lag 20	-0.011	-1.440

wp31	0.002	1.430	lag 21	0.006	0.780
wp32	0.001	1.000	lag 22	-0.021	-2.830
			lag 23	-0.123	-16.440
			lag24	0.108	14.340
	Adj R-Sq	0.984			

Table 3.5: Winter load estimation results from step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	261.367	14.900	lag 1	-0.220	-29.090
trend	0.000	-0.270	lag 2	-0.070	-9.090
nycload1	0.941	351.100	lag 3	0.035	4.580
nycload24	0.076	9.770	lag 4	0.012	1.500
nycload25	-0.073	-9.480	lag 5	-0.018	-2.310
pnyc1	0.031	0.280	lag 6	0.001	0.190
pnyc24	4.231	29.080	lag 7	0.049	6.340
pnyc25	-4.004	-24.760	lag 8	0.011	1.450
c_24hour	-231.611	-72.660	lag 9	-0.035	-4.540
s_24hour	42.184	11.140	lag 10	-0.018	-2.380
c_12hour	-106.298	-51.800	lag 11	0.054	7.060
s_12hour	-102.265	-53.360	lag 12	0.086	11.160
c_6hour	-13.982	-11.040	lag 13	0.039	5.020
s_6hour	7.727	6.310	lag 14	-0.005	-0.700
c_week	6.719	3.100	lag 15	-0.004	-0.490
s_week	8.429	4.040	lag 16	0.033	4.280
weekend cycle	51.553	8.740	lag 17	0.070	9.100
cddc_24hour	0.667	1.910	lag 18	0.018	2.330
cdds_24hour	-1.071	-2.950	lag 19	-0.045	-5.820
cddc_week	0.006	0.020	lag 20	-0.002	-0.200
cdds_week	0.061	0.200	lag 21	0.062	8.060
cddweekendcycle	0.509	0.640	lag 22	0.031	4.030
cdd	1.669	2.120	lag 23	-0.106	-13.750
sq_cdd	-0.022	-0.860	lag24	0.074	9.840
wp31	0.013	0.660			
wp32	-0.011	-0.780			
	Adj R-Sq	0.9841			

Table 3.6: Winter price estimation results from step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	0.479	0.690	lag 1	0.007	0.930
trend	0.000	-0.990	lag 2	-0.014	-1.930
nycload1	0.000	2.280	lag 3	0.015	2.040
nycload24	0.002	6.540	lag 4	-0.001	-0.130
nycload25	-0.002	-7.760	lag 5	0.033	4.400
pnyc1	0.854	207.970	lag 6	0.001	0.180
pnyc24	0.655	109.900	lag 7	-0.035	-4.610
pnyc25	-0.551	-84.050	lag 8	-0.061	-8.170
c_24hour	-0.963	-10.220	lag 9	-0.046	-6.150
s_24hour	-0.401	-3.300	lag 10	-0.033	-4.380
c_12hour	-1.332	-18.760	lag 11	-0.028	-3.750
s_12hour	-0.311	-4.660	lag 12	0.022	2.890
c_6hour	0.799	17.210	lag 13	0.003	0.390
s_6hour	0.252	5.650	lag 14	-0.002	-0.280
c_week	0.368	4.160	lag 15	-0.008	-1.010
s_week	0.074	0.860	lag 16	-0.002	-0.270
weekend cycle	1.041	4.780	lag 17	0.008	1.040
cddc_24hour	-0.042	-5.220	lag 18	0.008	1.120
cdds_24hour	-0.046	-5.130	lag 19	0.025	3.370
cddc_week	0.011	0.930	lag 20	0.017	2.310
cdds_week	0.017	1.360	lag 21	-0.009	-1.160
cddweekendcycle	0.075	2.550	lag 22	0.013	1.710
cdd	-0.025	-0.850	lag 23	-0.112	-14.980
sq_cdd	0.005	4.530	lag24	0.102	13.570
wp31	0.002	1.840			
wp32	0.000	0.370			
	Adj R-Sq	0.970			

3.3.2 Estimating structural form

To solve for electricity load and price simultaneously, predicted value of load and price from step1 are estimated. Using these predicted values as endogenous variables, load and price are

estimated together. The estimation models for electricity load and price in summer and winter are explained below.

$$summer\_load_{it} = \beta_{i0} + \beta_{i1} t_t + + \beta_{i2} summer\_load1_t + \beta_{i3} summer\_load24_t + \beta_{i4} summer\_load25_t$$

$$+ \beta_{i5} ch_t + \beta_{i6} sh_t + \beta_{i7} cw_t + \beta_{i8} cw_t + \beta_{i9} weekend\ cycle + \beta_{i10} cdd_t * ch_t + \beta_{i11} cdd_t * sh_t$$

$$+ \beta_{i12} cdd_t * cw_t + \beta_{i13} cdd_t * sw_t + \beta_{i14} cdd_t * weekend\ cycle_t + \beta_{i15} cdd_t + \beta_{i16} sq\_cdd_t + v_{it}$$

$$v_{it} = -\varphi_1 v_{it-1} - \varphi_2 v_{it-2} - \cdots - \varphi_{24} v_{it-24} + u_{it}$$

$$winter\_load_{it} = \beta_{i0} + \beta_{i1} t_t + + \beta_{i2} winter\_load1_t + \beta_{i3} winter\_load24_t + \beta_{i4} winter\_load25_t$$

$$+ \beta_{i5} ch_t + \beta_{i6} sh_t + \beta_{i7} ch2_t + \beta_{i8} sh2_t + \beta_{i9} ch4_t + \beta_{i10} sh4_t + \beta_{i11} cw_t + \beta_{i14} cw_t$$

$$+ \beta_{i12} weekend\ cycle + \beta_{i13} newhdd_t * ch_t + \beta_{i14} newhdd_t * sh_t + \beta_{i15} newhdd_t * cw_t + \beta_{i16} newhdd_t * sw_t$$

$$+ \beta_{i17} newhdd_t * weekend\ cycle_t + \beta_{i18} newhdd_t + \beta_{i19} sq\_newhdd_t + v_{it}$$

$$v_{it} = v_{it-1} - \varphi_2 v_{it-2} - \cdots - \varphi_{24} v_{it-24} + u_{it}$$

$$summer\_price_{it} = \beta_{i0} + \beta_{i1} t_t + \beta_{i2} pre\_summer\_load_t + \beta_{i3} summer\_load1_t + \beta_{i4} summer\_load24_t$$

$$+ \beta_{i5} summer\_load25_t + \beta_{i6} summer\_price1_t + \beta_{i7} summer\_price24_t + \beta_{i8} summer\_price25_t + \beta_{i9} ch_t$$

$$+ \beta_{i10} sh_t + \beta_{i11} cw_t + \beta_{i12} cw_t + \beta_{i13} weekend\ cycle + \beta_{i14} wp31_t + \beta_{i15} wp32_t + v_{it}$$

$$v_{it} = -\varphi_1 v_{it-1} - \varphi_2 v_{it-2} - \cdots - \varphi_{24} v_{it-24} + u_{it}$$

$$winter\_price_{it} = \beta_{i0} + \beta_{i1} t_t + \beta_{i2}\, pre\_winter\_load_t + \beta_{i3}\, winter\_load1_t + \beta_{i4}\, winter\_load24_t$$

$$+ \beta_{i5}\, winter\_load25_t + \beta_{i6}\, winter\_price1_t + \beta_{i7}\, winter\_price24_t + \beta_{i8}\, winter\_price25_t + \beta_{i9}\, ch_t$$

$$+ \beta_{i10}\, sh_t + \beta_{i11}\, ch2_t + \beta_{i12}\, sh2_t + \beta_{i13}\, ch4_t + \beta_{i14}\, sh4_t + \beta_{i15}\, cw_t + \beta_{i16}\, cw_t + \beta_{i17}\, weekend\ cycle$$

$$+ \beta_{i18}\, wp31_t + \beta_{i19}\, wp32_t + v_{it}$$

$$v_{it} = -\varphi_1 v_{it-1} - \varphi_2 v_{it-2} - \cdots - \varphi_{24} v_{it-24} + u_{it}$$

$pre\_summer\_load_t$ = predicted value of summer electricity load from step 1

$pre\_winter\_load_t$ = predicted value of winter electricity load from step 1

$pre\_summer\_price_t$ = predicted value of summer electricity price from step 1

$pre\_winter\_price_t$ = predicted value of winter electricity price from step 1

t_t = time trend

cw_t, and sw_t,: weekly pattern variables

(cosine and sine curves with week peroid)

$ch_t, sh_t, ch2_t, sh2_t, ch4_t, sh4_t$: daily pattern variables

(cosine and sine curves with 24 hour, 12 hour, and 6 hours peroid)

weekend cycle: 1 during week day and cosine curve during weekend

cdd_t, $newhdd_t$: heating degree days and new cooling degree days

$wp31_t, wp31_t$: weighted natural gas prices

Table 3.7: Summer load estimation results from step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	232.295	42.360	lag 1	-0.298	-39.360
trend	0.000	0.400	lag 2	-0.194	-24.640
nycload1	0.938	695.750	lag 3	0.040	5.010
nycload24	0.426	190.670	lag 4	0.009	1.090
nyloadc25	-0.413	-179.950	lag 5	0.046	5.900

c_24hour	-168.155	-121.090	lag 6	0.113	14.420
s_24hour	36.861	24.660	lag 7	0.005	0.580
c_week	3.657	2.960	lag 8	-0.096	-12.150
s_week	10.594	8.300	lag 9	-0.074	-9.340
weekend cycle	42.438	11.960	lag 10	0.027	3.440
cddc_24hour	-1.044	-8.820	lag 11	0.057	7.260
cdds_24hour	0.867	6.540	lag 12	-0.044	-5.560
cddc_week	0.332	2.790	lag 13	-0.065	-8.240
cdds_week	0.710	5.520	lag 14	0.041	5.250
cddweekendcycle	-0.982	-2.920	lag 15	0.092	11.660
cdd	7.294	20.420	lag 16	0.079	9.940
sq_cdd	0.046	4.870	lag 17	0.029	3.630
			lag 18	0.041	5.210
			lag 19	0.094	11.980
			lag 20	-0.022	-2.780
			lag 21	-0.126	-15.950
			lag 22	0.128	16.080
			lag 23	-0.095	-12.150
			lag24	0.026	3.380
	Adj R-Sq 0.998				

Table 3.8: Summer price estimation results from step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-2.373	-18.300	lag 1	-0.270	-35.710
trend	0.000	6.770	lag 2	-0.187	-23.880
pre_nycload	0.005	32.910	lag 3	-0.144	-18.530
nycload1	-0.004	-26.600	lag 4	0.124	15.810
nycload24	0.002	20.980	lag 5	0.034	4.330
nycload25	-0.002	-31.440	lag 6	-0.035	-4.490
pnyc1	0.882	803.830	lag 7	0.034	4.300
pnyc24	0.534	429.440	lag 8	-0.058	-7.420
pnyc25	-0.463	-320.390	lag 9	-0.044	-5.590
c_24hour	-1.248	-22.350	lag 10	0.127	16.190
s_24hour	-0.574	-10.490	lag 11	0.074	9.380
c_week	0.117	4.860	lag 12	-0.006	-0.790
s_week	-0.032	-1.380	lag 13	-0.109	-13.820
weekend cycle	0.320	5.890	lag 14	0.065	8.190
wp31	0.001	3.290	lag 15	0.042	5.320
wp32	0.001	3.89	lag 16	0.123	15.750

	lag 17	-0.006	-0.770
	lag 18	0.012	1.570
	lag 19	0.024	3.070
	lag 20	-0.084	-10.660
	lag 21	-0.094	-11.960
	lag 22	-0.205	-26.300
	lag 23	0.039	4.960
	lag24	0.062	8.180
Adj R-Sq 0.999			

Table 3.9: Winter load estimation results from step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	255.077	36.980	lag 1	-0.220	-29.090
trend	0.000	-7.190	lag 2	-0.070	-9.090
nycload1	0.957	951.810	lag 3	0.035	4.580
nycload24	0.077	32.280	lag 4	0.012	1.500
nycload25	-0.082	-34.830	lag 5	-0.018	-2.310
c_24hour	-245.221	-201.590	lag 6	0.001	0.190
s_24hour	51.596	32.820	lag 7	0.049	6.340
c_12hour	-128.436	-194.420	lag 8	0.011	1.450
s_12hour	-104.330	-175.040	lag 9	-0.035	-4.540
c_6hour	-3.717	-11.090	lag 10	-0.018	-2.380
s_6hour	10.616	31.600	lag 11	0.054	7.060
c_week	3.992	4.420	lag 12	0.086	11.160
s_week	9.778	11.220	lag 13	0.039	5.020
weekend cycle	32.323	14.430	lag 14	-0.005	-0.700
hddc_24hour	0.444	3.410	lag 15	-0.004	-0.490
hdds_24hour	-0.819	-5.990	lag 16	0.033	4.280
hddc_week	-0.192	-1.610	lag 17	0.070	9.100
hdds_week	-0.052	-0.410	lag 18	0.018	2.330
hddweekendcycle	1.141	3.690	lag 19	-0.045	-5.820
hdd	1.343	4.270	lag 20	-0.002	-0.200
sq_hdd	-0.036	-3.350	lag 21	0.062	8.060
			lag 22	0.031	4.030
			lag 23	-0.106	-13.750
			lag24	0.074	9.840
	Adj R-Sq 0.984				

Table 3.10: Winter price estimation from step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-0.336	-1.140	lag 1	-0.140	-18.530
trend	0.000	-2.920	lag 2	-0.378	-51.050
pre_load	0.001	7.320	lag 3	0.024	3.040
nycload1	-0.001	-4.990	lag 4	0.119	15.170
nycload24	0.002	47.720	lag 5	0.031	3.900
nycload25	-0.002	-52.640	lag 6	-0.044	-5.630
pnyc1	0.868	932.680	lag 7	-0.123	-15.750
pnyc24	0.587	508.440	lag 8	-0.086	-10.990
pnyc25	-0.515	-407.490	lag 9	0.006	0.810
c_24hour	-1.034	-29.490	lag 10	0.056	7.180
s_24hour	-0.492	-13.770	lag 11	0.084	10.770
c_12hour	-1.454	-62.090	lag 12	-0.087	-11.200
s_12hour	-0.376	-17.350	lag 13	-0.089	-11.430
c_6hour	0.941	134.270	lag 14	-0.060	-7.640
s_6hour	0.311	45.750	lag 15	-0.107	-13.720
c_week	0.314	10.600	lag 16	0.027	3.400
s_week	0.097	3.410	lag 17	0.135	17.240
weekend cycle	1.123	24.120	lag 18	0.028	3.570
wp31	0.002	3.260	lag 19	-0.164	-20.930
wp32	0.001	2.520	lag 20	0.018	2.250
			lag 21	0.064	8.140
			lag 22	0.134	16.990
			lag 23	-0.252	-34.020
			lag24	0.000	0.010
	Adj R-Sq 0.999				

The overall performance of these estimated models is very good. All adjusted R-sq are over 0.98 and most variables are statistically meaningful and satisfactorily explain load and price behavior in both summer and winter. When compared to the results from Chapter 1, we can conclude that load and price estimation in Chapter 3 is improved because dynamic terms (lagged

loads and prices) are included in the model and these terms better explain electricity load and price movement.

To determine the impact of load on price equation, we calculate the long run price electricity of load (LRE). The hottest and coldest days (July 6, 2010 and January 16, 2009, respectively) are selected from within the observation period and used to calculate the LRE.

$\frac{1-\beta_{i6}-\beta_{i7}-\beta_{i8}}{\beta_{i2}+\beta_{i3}+\beta_{i4}+\beta_{i5}} * \frac{Price}{Load}$ is defined as the LRE. From Table 3.11, it is known that electricity load increases price and that in New England, LRE in winter is bigger than that of summer. On the other hand, in two NY state regions, LRE in summer is larger than that of winter

Table 3.11 Long-run price elasticity of electricity load

	NE1	NE2	Boston	NY1	NY2	NYC
LRE(07/06/2010)	0.611	0.472	0.472	0.868	0.438	0.458
LRE(01/16/2009)	0.964	0.880	0.913	0.942	0.338	0.438

Tables 3.12 and 3.13 summarize the natural gas coefficients for each of the six regions in summer (07/06/2010) and winter (01/16/2009). It is observed that the wp31 at lag 0 impacts electricity price more than the wp32 at lag one week. When we compare the summer and winter impact of natural gas prices on electricity price, it is concluded that there is no significant difference.

Table 3.12 Parameter estimates of the weighted sum of natural gas price in summer

	NE1	NE2	Boston	NY1	NY2	NYC
wp31(β_{14})	0.00844	0.00639	0.00577	0.00121	0.000021	0.00132
	(5.72)	(4.82)	(4.26)	(11.26)	(0.06)	(3.29)
wp32(β_{15})	0.00331	0.00448	0.00477	0.00198	0.001877	0.00125
	(2.83)	(4.25)	(4.43)	(22.98)	(7.34)	(3.89)

Table 3.13 Parameter estimates of the weighted sum of natural gas price in winter

	NE1	NE2	Boston	NY1	NY2	NYC
wp31(β_{18})	0.00647	0.0101	0.00993	0.00016	0.001477	0.00174
	(4.86)	(9.28)	(9.63)	(0.68)	(4.9)	(3.26)
wp32(β_{19})	0.00438	0.00107	0.00112	0.001	0.00047	0.00097
	(4.15)	(1.36)	(1.51)	(5.81)	(2.19)	(2.52)

To determine the long-run price elasticity of natural gas prices (LREN) each parameter estimate is multiplied by the weight we calculated in chapter 1(w_{1i} and w_{2i}). Therefore, $\{\sum_{i=0}^{336}(\beta_{14}w_{1i}+\beta_{15}w_{2i})$ *natural gas price/electricity price} is defined as the summer long-run price elasticity of natural gas and $\{\sum_{i=0}^{336}(\beta_{18}w_{1i}+\beta_{19}w_{2i})$ *natural gas price/electricity price} is defined as the winter long-run price elasticity of natural gas.

Table 3.14 Long-run price elasticity of natural gas

	NE1	NE2	Boston	NY1	NY2	NYC
LREN(07/06/2010)	0.098	0.091	0.091	0.047	0.023	0.025
LREN(01/16/2009)	0.123	0.116	0.117	0.010	0.016	0.023

From Table 3.14, it is noted that in New England, the long-run price elasticity of natural gas in winter is higher than in summer. On the other hand, in NY the long-run impact of natural gas prices is greater on summer electricity prices than on winter prices.

3.3.3 TSL in summer and winter

From the final electricity load and price estimation results, total electricity load in summer and winter is divided into TSL and N-TSL. First of all, in case of summer, the summer prediction in 04/02/2007 at 1 hour is estimated using actual values of the lagged loads. Then the predicted lags are used to predict one step ahead all the way through the summer. To get the N-TSL in 04/02/2007 at 1 hour, we set CDD is zero and estimate predicted N-TSL using predicted lagged loads. Next, the N-TSL in 04/02/2007 at 2 hour is estimated using the N-TSL in 04/02/2007 at 1 hour, 24 hour lagged load, and 25 hour lagged load. From 04/03/2007 at 2 hour, the N-TSL is estimated using all lagged N-TSLs which we already estimated. Finally the difference between total predicted load and estimate N-TSL is defined TSL.

The results are summarized in Tables 3.15 to 3.18. Tables 3.15 and 3.16 show the TSL proportion of the total load. NYC has the highest TSL during summer. The major source of the Summer Temperature-Sensitive Load (STSL) is air conditioning and the major source of the Winter Temperature-Sensitive Load (WTSL) is heating. NYC, with its high density of large buildings and resulting high demand for air conditioning give it the largest STSL ratio of the six regions.

Table 3.15: Total load and STSL ratio in summer

Area	Average total load per hour (MWh)	Average SNTSL per hour (MWh)	Average STSL per hour (MWh)	Ratio (%)
NE1	3270.80	2877.20	256.42	7.84
NE2	8507.10	7448.23	1046.90	12.31
Boston	3010.80	2679.55	327.03	10.86
NY1	6254.60	5750.18	495.06	7.92
NY2	6372.70	5564.50	799.79	12.55
NYC	6609.30	5474.47	1126.70	17.05

Table 3.16: Total load and WTSL ratio in winter

Area	Average total load per hour (MWh)	Average WNTSL per hour (MWh)	Average WTSL per hour (MWh)	Ratio
NE1	3357.70	3167.05	185.50	5.52
NE2	8336.10	7639.73	683.97	8.20

Boston	2945.30	2739.15	202.25	6.87
NY1	6477.80	5918.86	550.04	8.49
NY2	5799.70	5399.80	391.47	6.75
NYC	5800.00	5564.35	228.32	3.94

The TSL ratio for daily peak load is also calculated and the results are shown in Tables 3.17 and 3.18. First of all, we selected the highest peak load during a day and calculated the average peak load and average STSL at peak. The TSL ratios based on peak load are larger than those in Tables 3.15 and 3.16 which are based on total load. Since peak loads mostly occur when temperatures are high during summer, the TSL ratio based on peak load is higher than normal. In system operator's view, managing the STSL at peak is very important and meaningful. If the STSL at peak is controlled, we save the cost for constructing power plant to meet the peak load and maintaining system adequacy.

Table 3.17: Peak load and STSL ratio in summer

Area	Average peak load(MWh)	Average SNTSL at peak(MWh)	Average STSL at peak(MWh)	Ratio
NE1	3830.00	3391.56	371.26	9.69
NE2	10217.00	8656.93	1553.50	15.21
Boston	3565.70	3106.35	457.13	12.82
NY1	7157.00	6392.11	759.03	10.61

NY2	7741.30	6585.89	1151.70	14.88
NYC	7738.60	6341.61	1393.80	18.01

Table 3.18: Peak load and WTSL ratio in winter

Area	Average peak load(MWh)	Average WNTSL at peak(MWh)	Average WTSL at peak(MWh)	Ratio
NE1	4026.20	3691.45	332.60	8.26
NE2	10053.00	9225.77	819.93	8.16
Boston	3471.40	3228.18	241.32	6.95
NY1	7412.90	6729.54	678.45	9.15
NY2	7102.30	6530.86	566.01	7.97
NYC	6799.60	6466.2	330.07	4.85

The STSL is totally different from month. To find out this monthly difference, the STSL by difference months is calculated among six regions. We calculated the average STSL by different month and these results are summarized in Table 3.19. From the Table 3.19, it is known that STSL in July is the highest except NY1 area. STSL in September is the smallest and it is about 1/3 of the July's STSL all six regions.

Table 3.19: STSL and ratio for each month

	June		July		August		September	
Area	STSL (MWh)	Ratio (%)	STSL (MWh)	Ratio (%)	STSL (MWh)	Ratio (%)	STSL (MWh)	Ratio (%)
NE1	175.763	5.384	451.631	12.734	443.959	12.587	137.227	4.257
NE2	1000.20	11.589	2010.10	20.804	1798.50	19.109	576.593	7.038
Boston	287.254	9.483	612.218	18.209	555.375	16.854	194.920	6.632
NY1	479.132	7.551	775.510	11.665	817.352	12.277	293.155	4.777
NY2	829.363	12.561	1644.60	22.134	1445.30	20.047	398.151	6.458
NYC	1325.50	19.314	2030.70	26.792	1839.10	24.960	954.650	14.690

3.3.4 TSL at the hottest day

From this chapter 3.3.4, we focused on the hottest day during the observation period. We have shown that TSL is very important component and the large portion of the peak load. If we control this TSL of the peak load, we manage system maximum load and save the capacity cost of building new power plants and transmission's congestion cost together. Therefore, finding the hottest day's TSL pattern and controlling this maximum load using thermal storage are very meaningful.

The hottest day (July 6, 2010) is selected from the observation period and is plotted for the total load, N-TSL, and TSL in summer for all six regions. Basically N-TSL has a specific pattern

which is followed by sine and cosine curves and STSL is very sensitive to temperature. When temperature is high, the STSL increases, because electricity is the only source for summer cooling and air conditioning. Therefore, it is natural that STSL is very affected by temperature.

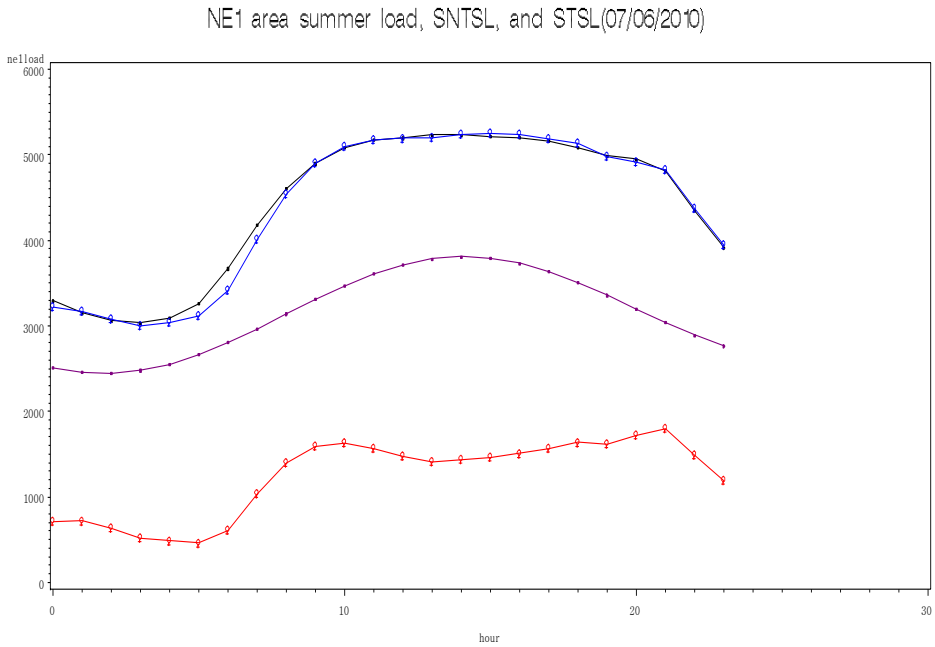

Figure 3.3: NE1 area summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

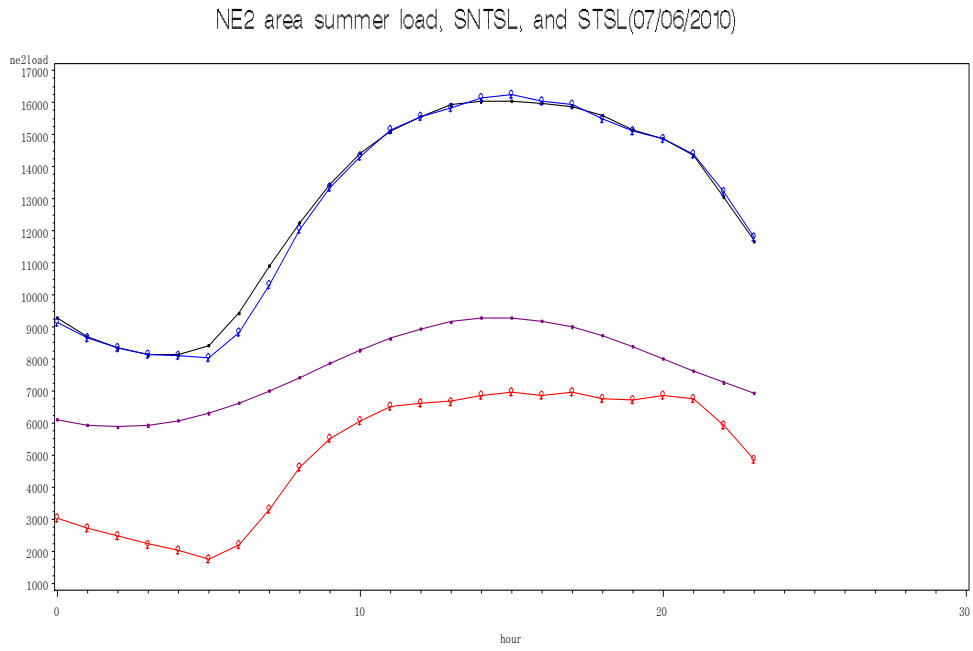

Figure 3.4: NE2 area summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

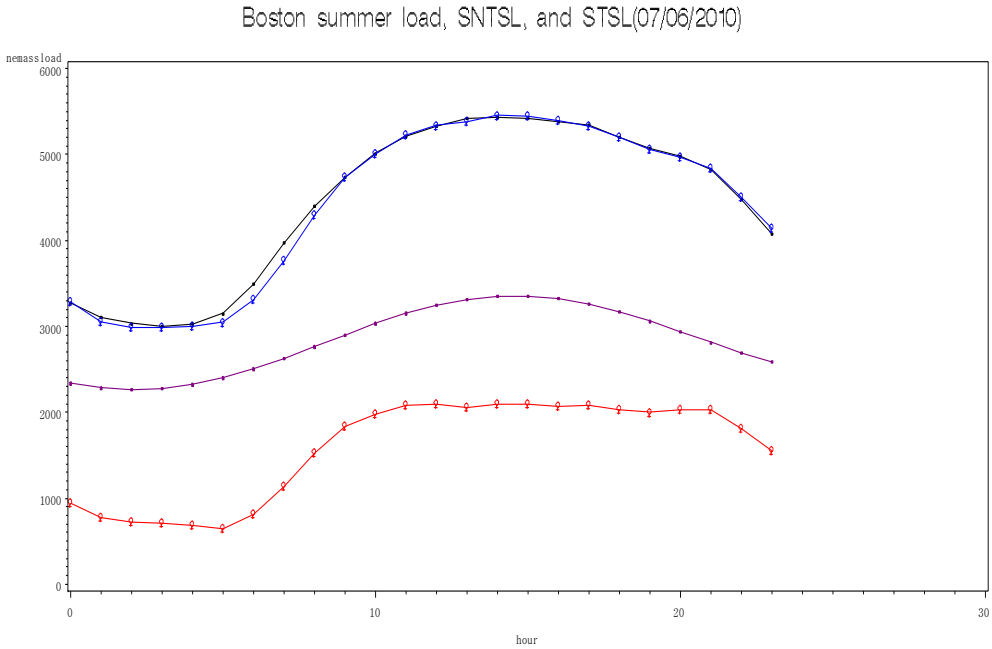

Figure 3.5: Boston summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

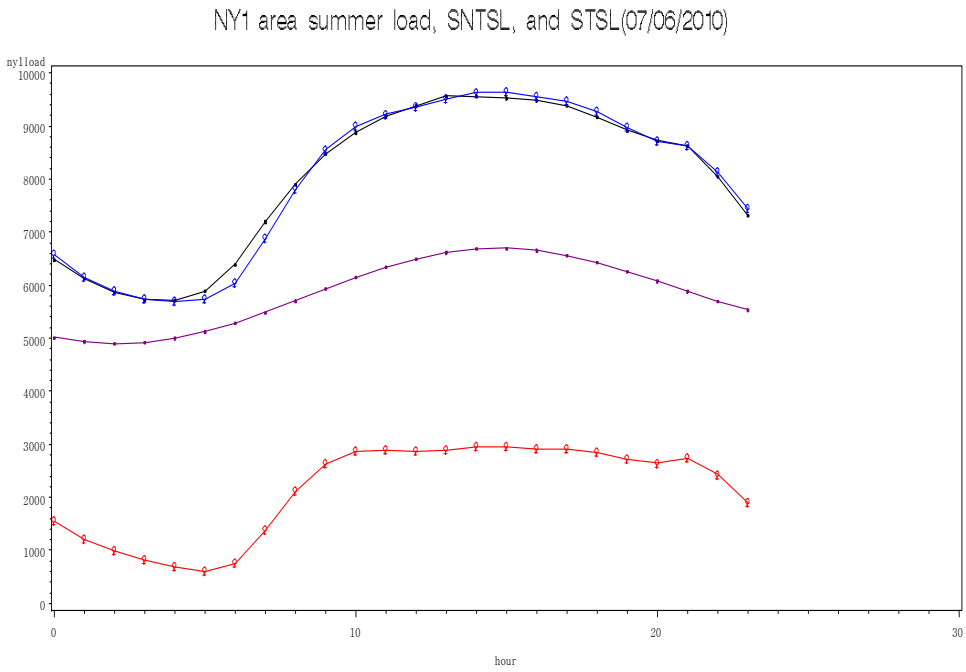

Figure 3.6: NY1 area summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

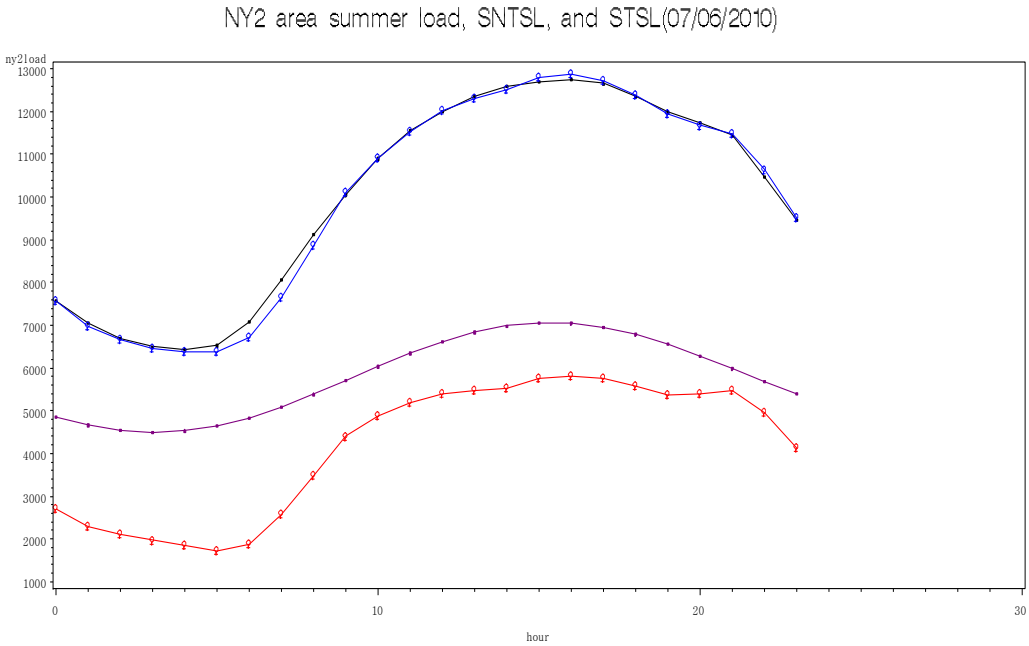

Figure 3.7: NY2 area summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

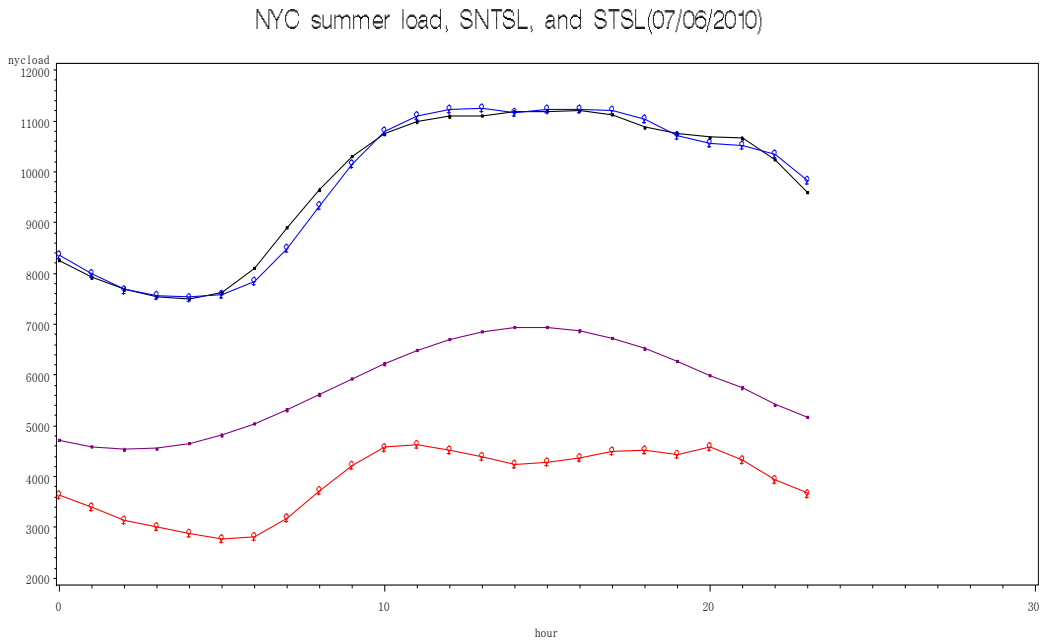

Figure 3.8: NYC summer load, SNTSL, and STSL (Unit: MWh)

(Black: base load, Blue: predicted value of load, Purple: SNTSL, Red: STSL)

3.4 Optimization model: energy cost minimization

Most STSL comes from air conditioning demand. If air conditioning demand is controlled, total electricity load is reduced and the load can be flattened. Finally, we can save the capacity cost of building new expensive power plants if we control the peak load during the summer. These days, thermal storage is highlighted as one of the most efficient ways to reduce STSL. For instance, ice batteries can be charged at night when electricity demand is low, and then melted during the day to provide cooling during high demand periods. To determine the most efficient use of the ice battery, we set up an energy cost minimization model to find the optimal energy benefit to consumers when thermal storage is introduced.

The object function is to minimize energy costs after introducing thermal storage. The ice battery is charged when the electricity price is low and discharged when the price is high. The decision variable x is the amount of charging or discharging of electricity using the ice battery. The electricity price estimation model from 3.2 is used. The electricity price model captures the long-run price movement using several seasonal patterns and cycles. In this part, we minimize one-day energy cost using the price estimation. To adjust the long-run price equation to a short-run equation, we divide the original price equation into three parts as below.

$$\text{Electricity price} = \frac{a}{\delta(L)} + \frac{\gamma(L)}{\delta(L)} * load_t + \frac{f(t)}{\delta(L)}$$

Where, $\delta(L)$ = lag operator for electricity price

$\gamma(L)$ = lag operator for electricity load

$f(t)$ = long-run price movement including seasonal cycles and natural gas movement

Table 3.20: Coefficients summery

Area	$\frac{a}{\delta(L)}$	$\frac{\gamma(L)}{\delta(L)}$
NE1	19.28	0.0204
NE2	32.62	0.0062
Boston	33.64	0.0173
NY1	25.72	0.0116
NY2	28.01	0.0052
NYC	37.66	0.0061

Therefore, the short-run price equation is simply a function of load and short-run intercept which has to be adjusted. We assume that battery capacity (BC) is 30% of the sum of STSL for one day and that six hours are needed to fully charge the battery (HC). Actually it's unrealistic to control all TSL so we assume that only 30% of TSL can be controlled in our optimization model. The hottest day (July 6, 2010) is selected for this optimization for all six regions. The resulting energy cost minimization model is shown below:

$$\underset{x_t}{Min}\left\{\frac{a}{\delta(L)}+\frac{\gamma(L)}{\delta(L)}*(load_t+x_t)\right\}*(load_t+x_t)$$

$$st\ \ 0\le\sum_{t=1}^{T}x_t\le BC\quad (BC=\sum_{i=0}^{23}STSL_i*0.3)$$

$$-HC\le x_t HC\ \ (HC=BC/6)$$

Table 3.21: Optimization results

Area	Old cost($)	New cost($)	Cost reduction($)	CRR[14] (%)
NE1	12,621,138	11,571,930	1,049,207	8.31
NE2	38,273,864	34,423,535	3,850,329	10.06
Boston	12,898,205	11,722,293	1,175,912	9.12
NY1	13,455,744	12,750,894	704,850	5.24
NY2	23,761,280	21,494,498	2,266,782	9.54
NYC	24,366,927	22,980,619	1,386,308	5.69

[14] Cost Reduction Ratio

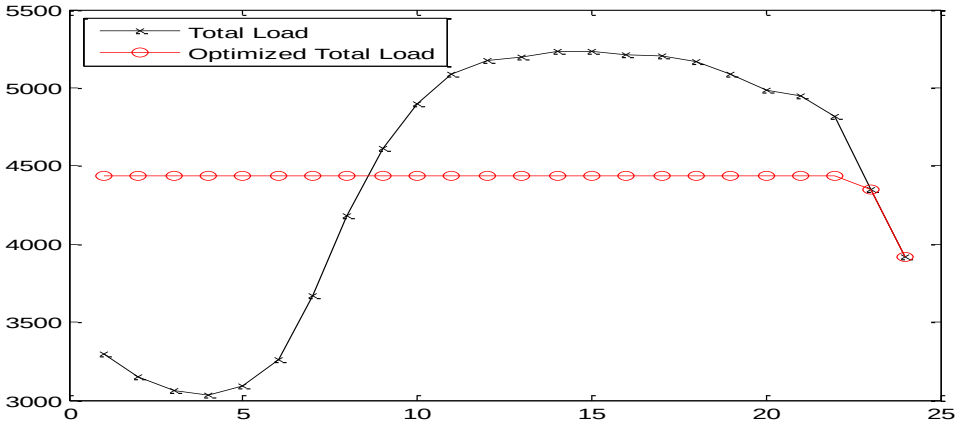

Figure 3.9: Optimized total load in NE1 (Unit: MWh)

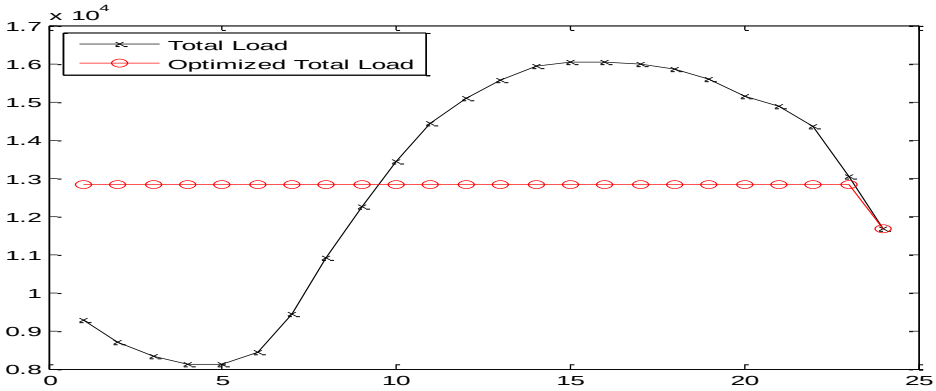

Figure 3.10: Optimized Total load in NE2 (Unit: MWh)

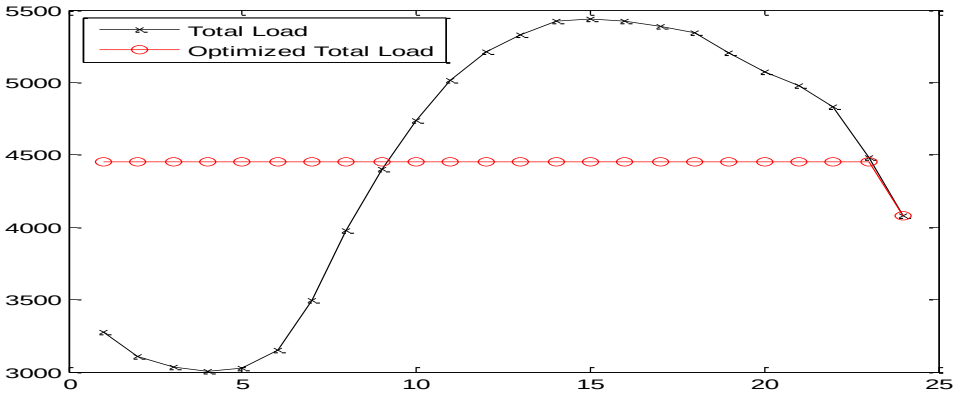

Figure 3.11: Optimized total load in Boston (Unit: MWh)

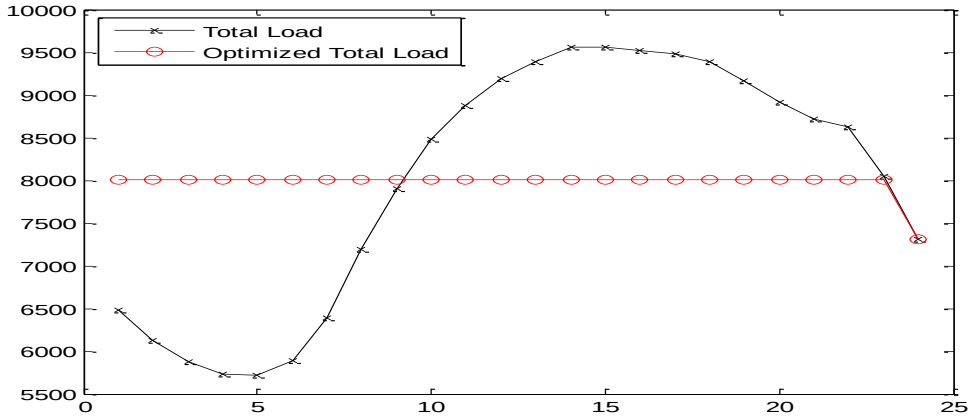

Figure 3.12: Optimized total load in NY1 area (Unit: MWh)

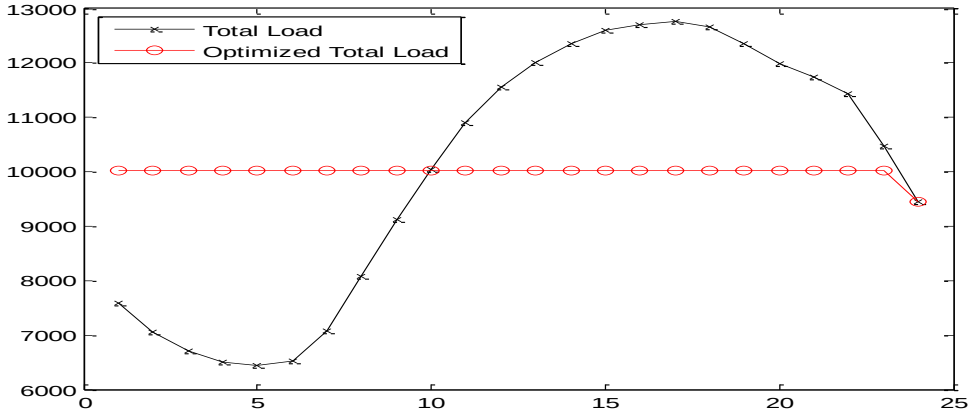

Figure 3.13: Optimized Total load in NY2 (Unit: MWh)

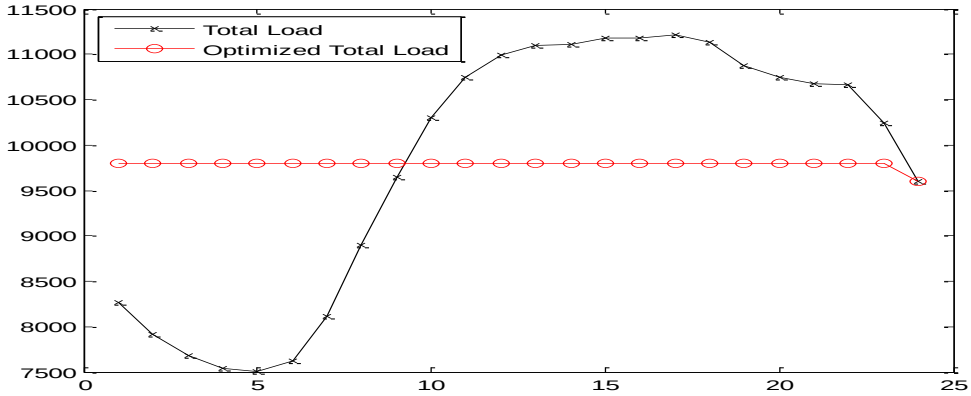

Figure 3.14: Optimized total load in NYC (Unit: MWh)

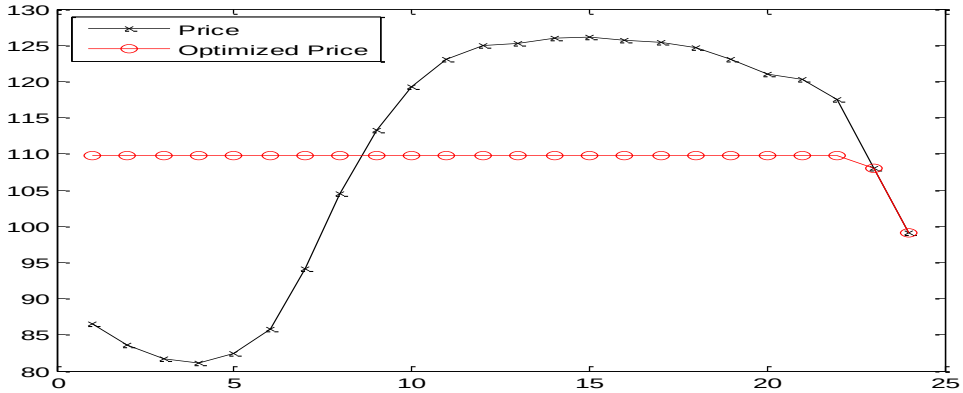

Figure 3.15: Optimized price in NE1 (Unit: MWh)

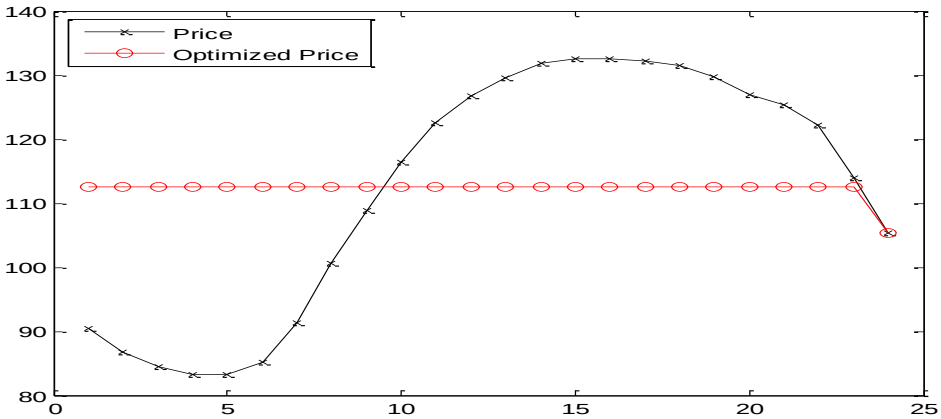

Figure 3.16: Optimized price in NE2 (Unit: MWh)

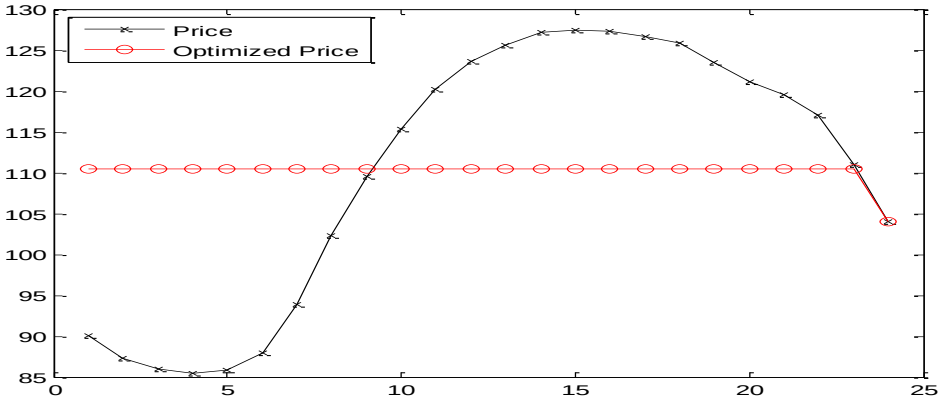

Figure 3.17: Optimized price in Boston (Unit: MWh)

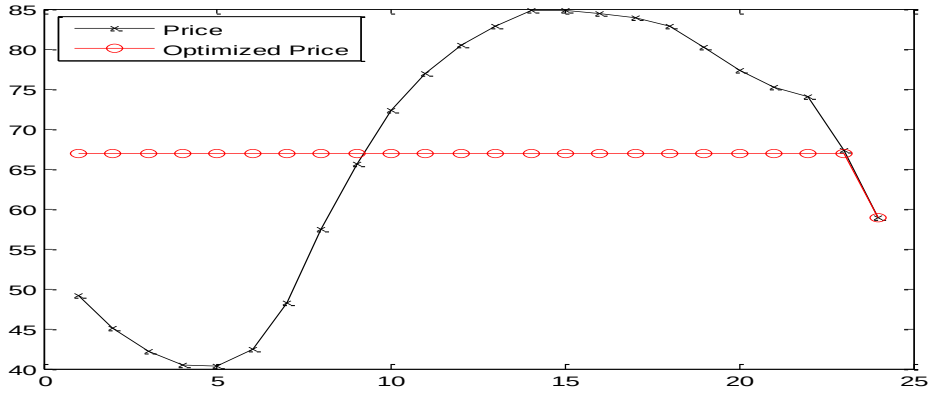

Figure 3.18: Optimized price in NY1 (Unit: MWh)

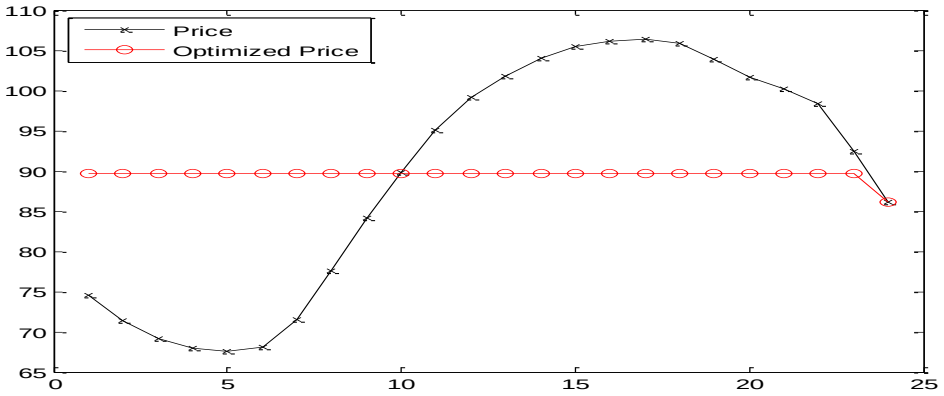

Figure 3.19: Optimized price in NY2 (Unit: MWh)

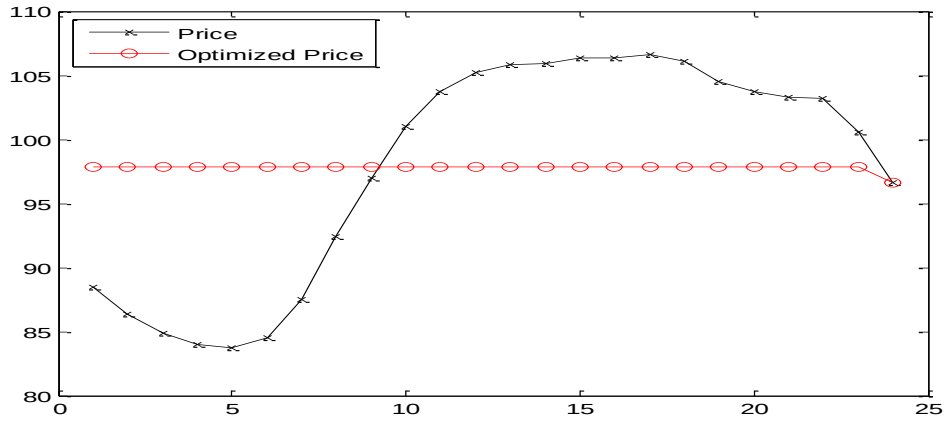

Figure 3.20: Optimized price in NYC (Unit: MWh)

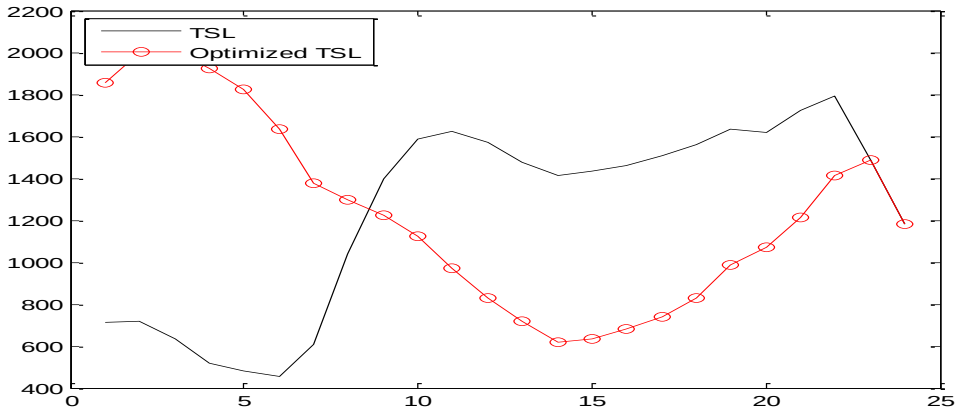

Figure 3.21: Optimized STSL in NE1 (Unit: MWh)

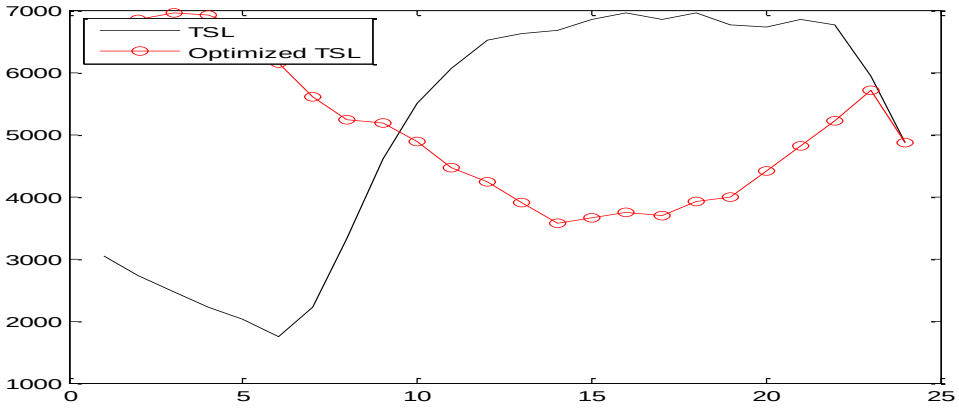

Figure 3.22: Optimized STSL in NE2 (Unit: MWh)

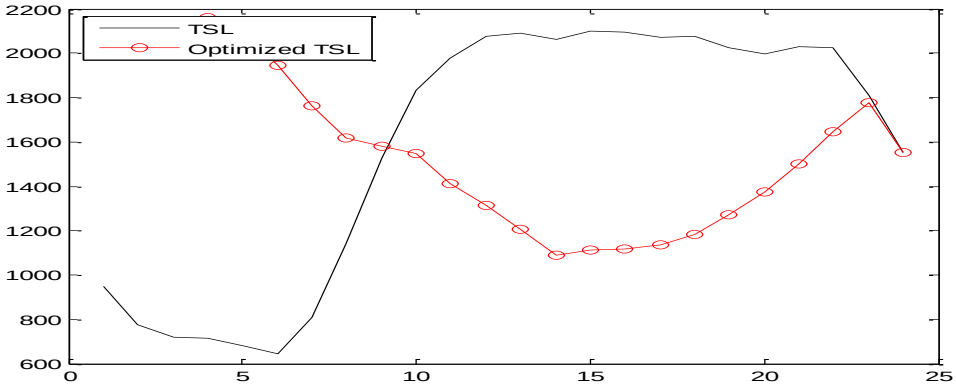

Figure 3.23: Optimized STSL in Boston (Unit: MWh)

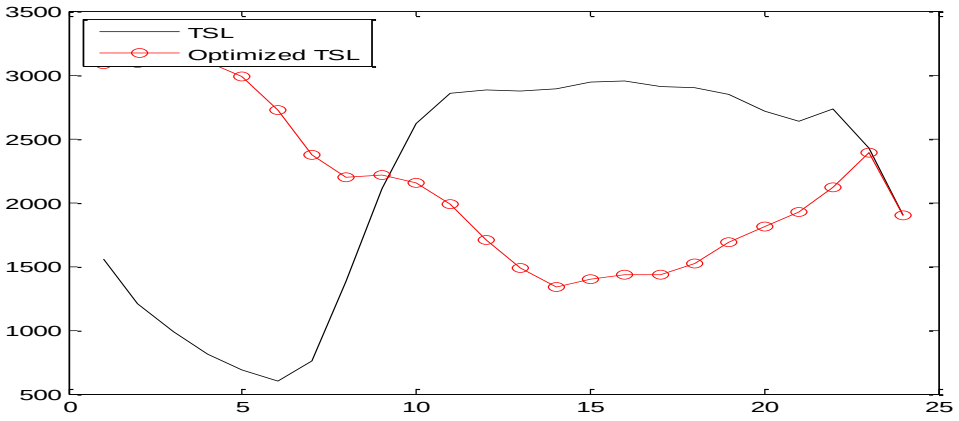

Figure 3.24: Optimized STSL in NY1 (Unit: MWh)

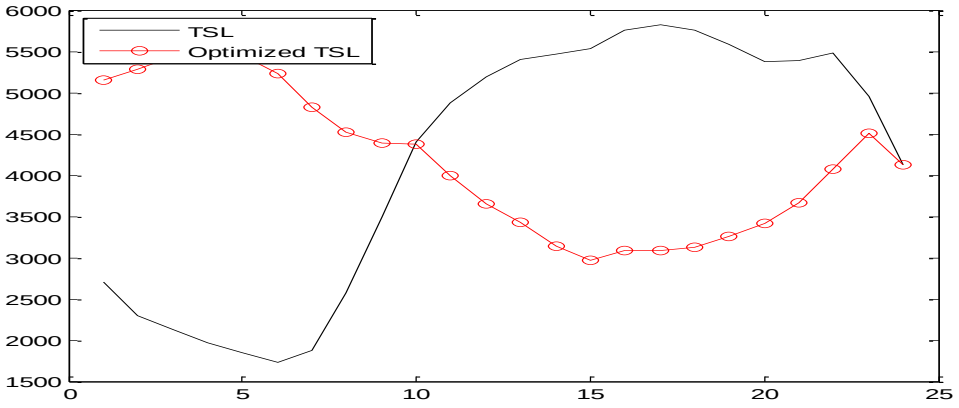

Figure 3.25: Optimized STSL in NY2 (Unit: MWh)

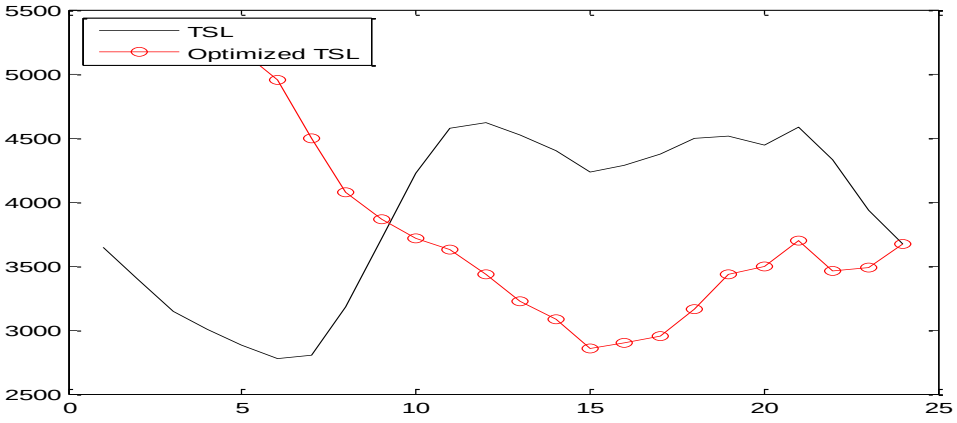

Figure 3.26: Optimized STSL in NYC (Unit: MWh)

Figures 3.9 to 3.26 show the energy cost minimization results. If battery capacity is 30% of total STSL, the total load among the six areas can be flattened and electricity prices also even out. In the case of STSL, nightly electricity demand for charging ice batteries increases dramatically. On the other hand, peak STSL decreases. Finally, peak STSL occurs at night while previous peak load disappears. To summarize, the energy cost is reduced 5.6% to 10% in all six regions.

Energy cost minimization results depend on battery capacity. Initially it is assumed that battery capacity is 30% of total STSL. To determine the effect of battery capacity on the optimization results, battery capacity is changed from 10% of STSL to 30% of STSL.

Table 3.22 shows the optimization results for different battery capacities. The plot for load and price in all regions are summarized in APPENDIX B. As we explained above, the cost reduction with 30% battery capacity is the greatest but the energy cost reductions are very similar for capacities of 10% and 20%. It was explained that the optimized load and price are totally flat under the 30% of STSL sum battery capacity case, and these flat profiles offset the money gaining opportunity using price differences off-peak at night and on-peak during the day. Therefore, the cost reduction effect gets smaller as more battery capacity is added. In particular, the reductions from 20% to 30% are small and unlikely to cover the capital cost of a bigger battery.

Table 3.22: Percentage energy Cost Reduction Ratio (CRR) for different battery capacities

Area	CRR (%) (10% of STSL)	CRR (%) (20% of STSL)	CRR (%) (30% of STSL)
NE1	7.19	8.06	8.31
NE2	8.81	9.89	10.06
Boston	8.20	9.01	9.12
NY1	3.60	4.89	5.24
NY2	8.38	9.41	9.54
NYC	5.54	5.69	5.69

In addition to this energy cost reduction, we also get a benefit from the capacity cost reduction caused by reduced peak load. If efficient battery use is achieved, peak load can be reduced, and the extra generating capacity needed during traditional peak times will no longer be necessary. This translates into significant reductions in capital and operating costs of 'peaking plants'. The total economic benefit is a combination of reducing new peak plant construction and reducing energy costs. The capacity cost reduction is calculated as follows:

$$\text{Capacity cost reduction} = \frac{(\text{Maximum system load}_t\,(A) - \text{optimized load}_t\,(B)) * 88{,}000\$/\text{Mwh}}{100\ \text{day}}$$

We assume that the annual capacity cost for a natural gas plant is 88,000$/MWh and this cost is allocated to 100 hot summer days.

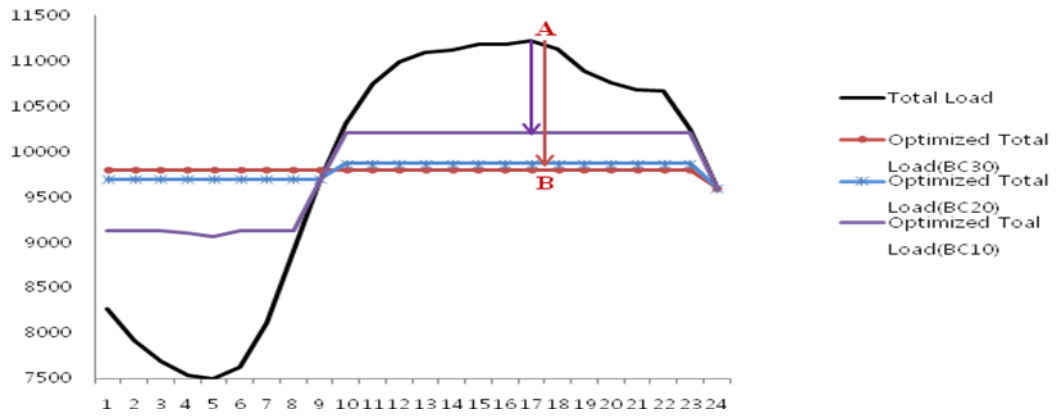

Figure 3.27: Peak load reduction under different battery capacities in NYC (Unit: MWh)

Finally, the total combined cost reductions from energy cost reduction and capacity cost reduction for the six regions are summarized in Table 3.23. Table 3.23 shows that 30% battery capacity gives the biggest total combined cost reduction, and the energy cost reductions are greater than the capacity cost reductions in all regions except NY1 area. However, Figure 3.28 also shows that the capacity cost reduction is more sensitive to battery capacity than the energy cost reduction. The explanation is that capacity cost reduction is caused by reduced peak load and the cost/MW does not change. On the other hand, the energy cost reduction is also decreased by the flattened price profile and the disappearance of the day/night price arbitrage.

Table 3.23: Total combined cost reduction under different battery capacities

Battery capacity	Energy cost reduction ($)	Capacity cost reduction ($)	Total cost reduction ($)
NE1			
10% of STSL sum	907,898.03	318,656.34	1,226,554.37
20% of STSL sum	1,017,093.74	523,104.15	1,540,197.89
30% of STSL sum	1,049,207.36	702,121.48	1,751,328.84

NE2			
10% of STSL sum	3,372,808.36	1,447,591.98	4,820,400.34
20% of STSL sum	3,783,636.36	2,335,926.92	6,119,563.28
30% of STSL sum	3,850,329.05	2,834,431.39	6,684,760.44
Boston			
10% of STSL sum	1,058,289.73	460,970.87	1,519,260.60
20% of STSL sum	1,162,169.41	734,349.29	1,896,518.71
30% of STSL sum	1,175,911.94	869,166.69	2,045,078.63
NY1			
10% of STSL sum	485,040.98	677,385.50	1,162,426.48
20% of STSL sum	657,881.64	1,061,498.65	1,719,380.29
30% of STSL sum	704,849.96	1,367,509.10	2,072,359.06
NY2			
10% of STSL sum	1,990,264.18	1,289,542.47	3,279,806.65
20% of STSL sum	2,234,965.44	2,045,585.05	4,280,550.49
30% of STSL sum	2,266,782.49	2,399,924.83	4,666,707.32
NYC			
10% of STSL sum	1,349,392.94	894,017.34	2,243,410.27
20% of STSL sum	1,385,345.19	1,188,615.55	2,573,960.74
30% of STSL sum	1,386,308.21	1,246,854.10	2,633,162.32

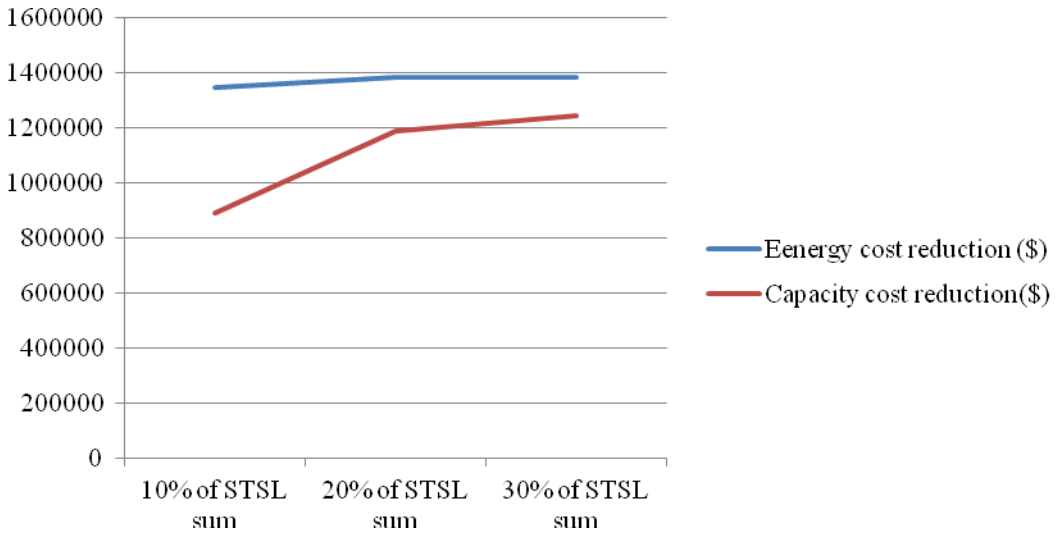

Figure 3.28: Cost reduction under different battery capacities in NYC (Unit: dollars)

Up to this point in the analysis it was assumed that all households[15] in NY State and New England own a thermal storage system and optimize their purchase of energy. However, in this part of the analysis it is assumed that there are two types of households, each constituting 50% of the total: those who own a thermal storage system and those who do not. The load profile for thermal storage owned customers is the sum of half of basic load and the new charge or discharge electricity amount using the thermal storage. On the other hand, the load profile for customers who don't own the thermal storage is just half of basic load. Even when a household does not have thermal storage, their electricity costs can be reduced when other households modify the daily pattern of system load and price. We assume that a household with a thermal storage unit has doubled the battery capacity compared to the previous situation. We can now calculate the benefits for two different types of household.

[15] The number of Boston households is 239,528 and in NYC, 598,362.

A table 3.24 summarizes the benefit for both types of household in NYC and Boston under different battery capacities. Generally, the benefit for Boston households is greater than it is for NYC. Under 10% and 20% of battery capacities, the energy cost reduction for thermal storage owners is greater than households who don't own thermal storage. On the other hand, considering only the energy cost reduction, both types of household in NYC and Boston benefit equally under 30% of battery capacity. This can be explained by the fact that load and price are totally flattened under 30% of battery capacity and peak and off-peak prices are the same. Any extra benefit gained from charging or discharging activity using thermal storage is shared between the two types of household. On the other hand, if the capacity cost reduction is allocated on the basis of the demand at the system peak to the households who own thermal storage, the thermal storage owner's total benefit is greater than non-thermal storage owners in both cases. This could provide an effective incentive to install thermal storage in homes. Therefore, it is essential to modify regulatory policy and allocate the benefit from the reduced system peak load to thermal storage owners.

Table 3.24: Optimization results for two different types of households

Battery capacity	Energy cost reduction($)		Capacity cost reduction($)		Total reduction($)	
NYC	household with thermal	household without thermal	household with thermal	household without thermal	household with thermal	household without thermal
10% of STSL sum	2.255	2.150	2.988	0	5.243	2.150
20% of STSL sum	2.315	2.291	3.973	0	6.288	2.291
30% of STSL sum	2.317	2.317	4.168	0	6.484	2.317
Boston	household with thermal	household without thermal	household with thermal	household without thermal	household with thermal	household without thermal

10% of STSL sum	4.418	4.085	3.849	0	8.267	4.085
20% of STSL sum	4.852	4.634	6.132	0	10.984	4.634
30% of STSL sum	4.909	4.909	7.257	0	12.167	4.909

3.5 Conclusion

These days there are several types of thermal energy storage systems being developed to conserve electricity. A promising type of thermal storage utilizes ice which is made using electricity during non-peak hours and then melted to cool temperatures during the day. Using this ice battery it is possible to lower the demand for electricity created by traditional air cooling systems and flatten the current electricity load. To control the summer electricity load using thermal storage, the total electricity load is divided into Non-Temperature Sensitive Load (N-TSL) and Temperature Sensitive Load (TSL) since TSL is the only load that can be controlled by using an ice battery.

In Section 3.2, it is shown that Summer TSL (STSL) is much larger than Winter TSL (WTSL) as expected. In winter, electricity is not the only or even a major energy source for heating. It is also concluded that STSL varies according to geographical region. The area with the biggest STSL ratio is NYC. The NE1 area has the smallest STSL ratio among the six regions. There are two factors which explain this. First there is the temperature effect on load, which is the strongest in NYC when the six regions are compared using the load estimation model. Second, the large number of buildings and high population density in NYC cause an unusually high demand for air conditioning and increased STSL.

Using the STSL from Section 3.2, an energy cost minimization model was developed in Section 3.3. Basically, STSL is the amount of electricity that can be controlled using thermal storage in the summer. If an ice battery is used, electricity demand is controlled and ice is made at night when the electricity price is low and then melted during the day to cool air for space conditioning systems. Therefore, by controlling the high STSL it is possible to flatten the total electricity load and price simultaneously. Given the reduced peak load caused by the thermal storage, the capacity cost of conventional generating capacity is reduced dramatically.

To minimize energy costs using this type of thermal storage, the battery capacity is determined as a proportion of the STSL. It is assumed that the ice battery capacity is 30% of the total daily STSL. The hottest day during the observation period is selected for this simulation and it is found that the total electricity load and price are totally flattened in all six regions at 30% of the STSL capacity. On the other hand, if the battery capacity is decreased, the optimized load and price are not fully flattened and the energy cost and capacity reduction effects are smaller. In general the cost reductions in all six regions are substantially larger going from 10% to 20% than they are going from 20% to 30%.

In the final part of the analysis, two different types of households are identified based on the ownership of thermal storage and the benefits of thermal storage are calculated for both types of household. Using 30% of the STSL for thermal storage, the value of the capacity cost reduction is roughly twice as large as the energy cost reduction for households with thermal storage in Boston and NYC. The overall conclusion is that it is important to modify the way that households pay for electricity so that they get direct economic benefits from reducing their

demand on peak compared to households with no thermal storage. To get the true benefit, it is necessary to develop a market system in which all participants pay for the services they use and get paid for the services they provide. Under this mechanism, deregulated electricity markets will be more efficient and total social benefits will be increased. The analysis in this chapter has shown clearly that the potential amount of thermal storage is sufficiently large, unlike the batteries in PHEVs, to completely flatten the daily pattern of load in the summer in the northeastern states.

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APPENDIX A

Table A.1 to A.40: electricity load and price estimation results in section 4.2

Table A.1: NE1 area summer load estimation results for step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	49.4885	8.64	lag 1	-0.85772	-113.51
trend	-4.27E-06	-0.08	lag 2	0.478169	48.02
ne1load1	0.9309	305.63	lag 3	-0.10044	-9.48
ne1load24	0.8466	209.21	lag 4	-0.00906	-0.85
ne1load25	-0.8004	-172.24	lag 5	0.044882	4.23
pne11	-0.0774	-4.22	lag 6	-0.0083	-0.78
pne124	-0.057	-3.21	lag 7	-0.04792	-4.51
pne125	-0.056	-3.11	lag 8	0.125757	11.83
c_24hour	-28.7441	-23.95	lag 9	-0.03494	-3.28
s_24hour	2.41	1.9	lag 10	-0.04046	-3.79
c_week	10.1254	10.34	lag 11	0.037133	3.48
s_week	3.5144	3.56	lag 12	0.000349	0.03
weekend cycle	24.5773	8.87	lag 13	0.005459	0.51
cddc_24hour	0.4266	2.63	lag 14	-0.0325	-3.05
cdds_24hour	0.9075	4.02	lag 15	0.040385	3.79
cddc_week	-0.3308	-2.28	lag 16	0.033529	3.14
cdds_week	0.3041	2.06	lag 17	0.005737	0.54
cddweekendcycle	-1.7037	-4.22	lag 18	-0.01607	-1.51
cdd	2.9154	7.12	lag 19	0.012224	1.15
sq_cdd	0.0326	2.62	lag 20	0.010006	0.94
wp31	0.0425	3.33	lag 21	0.011825	1.11
wp32	-0.0257	-2.54	lag 22	0.034883	3.29
			lag 23	-0.02126	-2.13
			lag24	0.039212	5.19
	Adj R-Sq 0.9964				

Table A.2: NE1 area summer price estimation results for step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-14.6699	-9.76	lag 1	0.045083	5.96
trend	4.37E-05	1.88	lag 2	0.062723	8.29
ne1load1	0.00923	14.55	lag 3	-0.03564	-4.7
ne1load24	1.45E-02	18.36	lag 4	-0.05281	-6.97

ne1load25	-0.0186	-19.44	lag 5	-0.06755	-8.91
pne11	0.6524	113.28	lag 6	-0.02884	-3.8
pne124	0.1087	14.49	lag 7	-0.03773	-4.97
pne125	-0.0469	-6.2	lag 8	-0.03414	-4.49
c_24hour	0.4795	1.93	lag 9	-0.01815	-2.39
s_24hour	-0.3596	-1.26	lag 10	-0.02072	-2.73
c_week	0.1597	0.59	lag 11	-0.01904	-2.51
s_week	-0.8834	-3.19	lag 12	-0.02199	-2.89
weekend cycle	-0.3508	-0.64	lag 13	-0.00166	-0.22
cddc_24hour	-0.26	-8.07	lag 14	-0.01544	-2.03
cdds_24hour	0.3868	7.96	lag 15	0.0024	0.32
cddc_week	-0.0195	-0.63	lag 16	0.011	1.45
cdds_week	0.1264	4.08	lag 17	-0.01724	-2.27
cddweekendcycle	-0.1405	-1.83	lag 18	-0.03637	-4.79
cdd	0.0868	1.07	lag 19	-0.02796	-3.68
sq_cdd	0.0248	8.44	lag 20	-0.04822	-6.36
wp31	0.004032	0.91	lag 21	-0.04268	-5.63
wp32	0.006686	1.9	lag 22	-0.0188	-2.48
			lag 23	-0.03248	-4.29
			lag24	0.015559	2.06
		Adj R-Sq 0.8260			

Table A.3: NE1 area winter load estimation for step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	27.1661	5.13	lag 1	-0.8364	-110.62
trend	0.00007	1.3	lag 2	0.48727	49.49
ne1load1	0.955	373.86	lag 3	-0.13142	-12.51
ne1load24	6.94E-01	125.41	lag 4	-0.0072	-0.68
ne1load25	-0.6606	-114.81	lag 5	0.027066	2.57
pne11	-0.077	-4.36	lag 6	-0.00323	-0.31
pne124	0.0159	0.92	lag 7	-0.05388	-5.11
pne125	-0.0611	-3.49	lag 8	0.129455	12.26
c_24hour	-49.4793	-39.38	lag 9	-0.03185	-3
s_24hour	19.1327	15.3	lag 10	-0.04548	-4.29
c_12hour	-33.9802	-34.83	lag 11	0.062536	5.9
s_12hour	-21.19	-25.36	lag 12	0.035507	3.35
c_6hour	-7.6608	-9.65	lag 13	-0.01872	-1.76
s_6hour	12.5952	15.43	lag 14	-0.03198	-3.02
c_week	7.7867	8.88	lag 15	0.054534	5.15
s_week	3.6655	4.37	lag 16	0.019286	1.82
weekend cycle	11.3757	4.89	lag 17	-0.00524	-0.5

hddc_24hour	0.3177	0.6	lag 18	-0.01866	-1.77
hdds_24hour	1.0135	1.51	lag 19	-0.00922	-0.87
hddc_week	2.0707	4.63	lag 20	0.001745	0.17
hdds_week	-0.2747	-0.57	lag 21	0.010778	1.02
hddweekendcycle	6.5837	5.02	lag 22	0.067564	6.43
hdd	-5.6428	-4.41	lag 23	-0.06435	-6.54
sq_hdd	0.0114	0.19	lag24	0.022212	2.94
wp31	0.0405	3.13			
wp32	-0.0264	-2.58			
	Adj R-Sq 0.9966				

Table A.4: NE1 area winter price estimation results for step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-18.3556	-10.25	lag 1	0.039271	5.19
trend	6.28E-05	2.83	lag 2	0.055375	7.32
ne1load1	0.0115	18.55	lag 3	-0.04005	-5.29
ne1load24	2.33E-02	15.47	lag 4	-0.05355	-7.07
ne1load25	-0.0283	-18.04	lag 5	-0.06548	-8.65
pne11	0.6655	116.64	lag 6	-0.02209	-2.91
pne124	0.1136	14.91	lag 7	-0.02776	-3.66
pne125	-0.0435	-5.68	lag 8	-0.02562	-3.38
c_24hour	0.9535	3.08	lag 9	-0.01083	-1.43
s_24hour	-0.2265	-0.68	lag 10	-0.01352	-1.78
c_12hour	1.7505	7.88	lag 11	-0.01274	-1.68
s_12hour	1.4358	7.71	lag 12	-0.01819	-2.4
c_6hour	0.1172	0.79	lag 13	0.00146	0.19
s_6hour	-0.3779	-2.41	lag 14	-0.01347	-1.78
c_week	0.0549	0.21	lag 15	0.003585	0.47
s_week	-0.5501	-2.18	lag 16	0.01346	1.77
weekend cycle	-1.6654	-3.23	lag 17	-0.01363	-1.8
hddc_24hour	-0.3559	-3.36	lag 18	-0.03577	-4.72
hdds_24hour	-0.0716	-0.47	lag 19	-0.02861	-3.77
hddc_week	0.1011	1	lag 20	-0.04977	-6.57
hdds_week	0.0287	0.26	lag 21	-0.04603	-6.08
hddweekendcycle	0.3811	1.36	lag 22	-0.02354	-3.11
hdd	0.072	0.24	lag 23	-0.03607	-4.77
sq_hdd	-0.0101	-0.66	lag24	0.015884	2.1
wp31	0.00565	1.31			
wp32	0.004758	1.39			
	Adj R-Sq 0.8226				

Table A.5: NE1 area summer load estimation results for step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	43.0185	15.7	lag 1	-0.34376	-45.67
trend	-0.000044	-2.29	lag 2	0.196762	24.71
ne1load1	0.9638	623.85	lag 3	0.003863	0.48
ne1load24	0.8672	342.06	lag 4	0.032959	4.08
ne1loadc25	-0.847	-305.95	lag 5	0.015493	1.91
c_24hour	-22.7273	-35.45	lag 6	-0.05142	-6.35
s_24hour	4.901	7.57	lag 7	0.076719	9.47
c_week	6.0496	12.81	lag 8	0.071079	8.75
s_week	2.926	6.09	lag 9	-0.01604	-1.97
weekend cycle	8.6499	6.13	lag 10	-0.01791	-2.21
cddc_24hour	0.0321	0.37	lag 11	0.008407	1.04
cdds_24hour	0.3844	3.19	lag 12	0.017261	2.13
cddc_week	-0.4747	-6.54	lag 13	-0.04127	-5.09
cdds_week	0.4047	5.42	lag 14	-0.00753	-0.93
cddweekendcycle	-2.7149	-12.9	lag 15	0.076572	9.45
cdd	3.1318	14.47	lag 16	0.058803	7.24
sq_cdd	-0.00054	-0.08	lag 17	-0.00355	-0.44
			lag 18	0.015619	1.93
			lag 19	0.004189	0.52
			lag 20	0.0204	2.52
			lag 21	0.04238	5.24
			lag 22	0.037917	4.68
			lag 23	0.020835	2.62
			lag24	0.095112	12.64
	Adj R-Sq 0.9974				

Table A.6: NE1 area summer price estimation results for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-16.0246	-28.03	lag 1	-0.88583	-117.36
trend	6.63E-05	7.7	lag 2	0.340519	33.97
pre_ ne1load	-0.000304	-0.87	lag 3	-0.2025	-19.66
ne1load1	0.0122	30.28	lag 4	0.109119	10.57
ne1load24	0.015	41.57	lag 5	-0.15334	-14.98
ne1load25	-0.0211	-53.88	lag 6	0.224161	21.93
pne11	0.6485	702.01	lag 7	-0.18337	-17.7

pne124	0.094	96.89	lag 8	0.146068	14.01
pne125	-0.0266	-27.65	lag 9	-0.1319	-12.66
c_24hour	-0.6752	-6.27	lag 10	0.175098	16.74
s_24hour	0.0389	0.32	lag 11	-0.1797	-17.05
c_week	-0.1393	-1.62	lag 12	0.1467	13.83
s_week	-0.4655	-5.58	lag 13	-0.09056	-8.54
weekend cycle	-1.7533	-10.89	lag 14	-0.01215	-1.15
wp31	0.008443	5.72	lag 15	-0.05221	-4.99
wp32	0.003311	2.83	lag 16	0.156267	15
			lag 17	-0.09204	-8.83
			lag 18	-0.02616	-2.53
			lag 19	0.173605	16.99
			lag 20	-0.20889	-20.4
			lag 21	0.179138	17.35
			lag 22	-0.13016	-12.64
			lag 23	-0.15495	-15.46
			lag24	0.058864	7.8
	Adj R-Sq 0.99600				

Table A.7: NE1 area winter load estimation results for step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	38.4645	19.19	lag 1	-0.26866	-35.53
trend	-4.50E-06	-0.26	lag 2	0.179927	22.98
ne1load1	0.9756	885.49	lag 3	-0.00592	-0.75
ne1load24	0.6724	165.83	lag 4	0.001737	0.22
ne1load25	-0.6597	-162.7	lag 5	-0.0022	-0.28
c_24hour	-51.7053	-67.31	lag 6	-0.06202	-7.83
s_24hour	22.8317	34.36	lag 7	0.075782	9.56
c_12hour	-36.7581	-62.53	lag 8	0.09127	11.48
s_12hour	-22.4002	-52.73	lag 9	-0.00977	-1.23
c_6hour	-8.1542	-15.06	lag 10	0.011383	1.43
s_6hour	13.6094	24.26	lag 11	0.082811	10.42
c_week	4.2669	11.38	lag 12	0.065161	8.17
s_week	3.2528	9.12	lag 13	-0.02903	-3.64
weekend cycle	-0.5655	-0.54	lag 14	0.010753	1.35
hddc_24hour	0.2261	0.77	lag 15	0.078913	9.93
hdds_24hour	1.0303	2.99	lag 16	0.047919	6.01
hddc_week	2.2161	10.08	lag 17	-0.01314	-1.65
hdds_week	-0.3041	-1.31	lag 18	-0.01945	-2.45
hddweekendcycle	7.7752	11.95	lag 19	-0.01757	-2.22
hdd	-6.7132	-10.29	lag 20	-0.00758	-0.96

sq_hdd	0.0308	0.9	lag 21	0.072375	9.14
			lag 22	0.047221	5.95
			lag 23	0.017049	2.18
			lag24	0.015224	2.01
	Adj R-Sq 0.9977				

Table A.8: NE1 area winter price estimation for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-18.8099	-42.75	lag 1	-0.72468	-96.19
trend	6.04E-05	9.25	lag 2	0.283128	30.6
pre_ ne1load	-0.001	-3.18	lag 3	-0.1362	-14.34
ne1load1	0.0136	39.23	lag 4	0.039233	4.15
ne1load24	0.0251	85.63	lag 5	-0.13828	-14.68
ne1load25	-0.0308	-99.96	lag 6	0.159241	16.92
pne11	0.6592	853.91	lag 7	-0.18373	-19.37
pne124	0.0919	119.77	lag 8	0.125221	13.12
pne125	-0.0242	-31.18	lag 9	-0.17121	-17.99
c_24hour	1.001	18.07	lag 10	0.169953	17.77
s_24hour	-0.0785	-1.14	lag 11	-0.19583	-20.31
c_12hour	1.7354	39.4	lag 12	0.121901	12.55
s_12hour	1.4662	34.27	lag 13	-0.12092	-12.45
c_6hour	0.1381	5.52	lag 14	-0.04716	-4.89
s_6hour	-0.3601	-13.79	lag 15	-0.12159	-12.72
c_week	-0.0531	-0.68	lag 16	0.156331	16.42
s_week	-0.544	-6.92	lag 17	-0.11978	-12.55
weekend cycle	-2.1478	-14.12	lag 18	0.012373	1.3
wp31	0.006473	4.86	lag 19	0.146087	15.53
wp32	0.004379	4.15	lag 20	-0.12179	-12.93
			lag 21	0.176788	18.69
			lag 22	-0.02666	-2.81
			lag 23	-0.14312	-15.47
			lag24	0.086389	11.47
	Adj R-Sq 0.9972				

Table A.9: NE2 area summer load estimation results for step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	143.9028	9.43	lag 1	-1.04654	-138.56
trend	-0.00015	-0.93	lag 2	0.558627	51.13

ne2load1	0.9347	323.52	lag 3	-0.15507	-13.26
ne2load24	8.26E-01	193.22	lag 4	-0.01204	-1.02
ne2load25	-0.7886	-169.55	lag 5	0.074949	6.38
p ne21	-0.162	-3.83	lag 6	-0.04762	-4.05
p ne224	-0.2013	-4.67	lag 7	0.007419	0.63
p ne225	-0.1381	-3.18	lag 8	0.104031	8.84
c_24hour	-82.7003	-21.15	lag 9	-0.04762	-4.04
s_24hour	-5.8042	-1.41	lag 10	-0.04381	-3.71
c_week	26.612	8.02	lag 11	0.040125	3.4
s_week	8.0888	2.39	lag 12	0.005361	0.45
weekend cycle	77.7593	8.27	lag 13	-0.02443	-2.07
cddc_24hour	-1.2083	-2.85	lag 14	0.007385	0.63
cdds_24hour	3.4836	6.44	lag 15	0.034644	2.94
cddc_week	-0.3531	-0.88	lag 16	0.059772	5.07
cdds_week	0.2726	0.65	lag 17	-0.02966	-2.52
cddweekendcycle	-3.5966	-3.17	lag 18	-0.00976	-0.83
cdd	7.996	7.06	lag 19	-0.00646	-0.55
sq_cdd	0.1199	3.64	lag 20	0.028445	2.42
wp31	0.0905	2.19	lag 21	-0.0152	-1.29
wp32	-0.0492	-1.51	lag 22	0.077973	6.66
			lag 23	-0.07437	-6.81
			lag24	0.049796	6.59
	Adj R-Sq 0.9979				

Table A.10: NE2 area summer price estimation results for step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-8.8896	-6.32	lag 1	0.029771	3.94
trend	0.000029	1.3	lag 2	0.052742	6.98
ne2load1	0.002952	13.74	lag 3	-0.0572	-7.55
ne2load24	0.005708	16.86	lag 4	-0.05331	-7.04
ne2load25	-0.00736	-19.65	lag 5	-0.04942	-6.52
pne21	0.6631	114.76	lag 6	-0.00517	-0.68
pne224	0.112	14.81	lag 7	-0.01615	-2.13
pne225	-0.0452	-5.92	lag 8	-0.02768	-3.65
c_24hour	-0.2226	-0.82	lag 9	-0.01233	-1.63
s_24hour	-1.5637	-5.08	lag 10	-0.01928	-2.54
c_week	0.0953	0.33	lag 11	-0.02062	-2.72
s_week	-0.8511	-2.87	lag 12	-0.02006	-2.64
weekend cycle	0.0403	0.07	lag 13	-0.00036	-0.05
cddc_24hour	-0.2103	-7.39	lag 14	-0.01764	-2.33
cdds_24hour	0.3151	7.64	lag 15	-0.0067	-0.88

cddc_week	-0.0634	-2.1	lag 16	0.018681	2.46
cdds_week	0.0885	2.85	lag 17	-0.01592	-2.1
cddweekendcycle	-0.1623	-2.14	lag 18	-0.02891	-3.81
cdd	-0.1112	-1.38	lag 19	-0.01925	-2.54
sq_cdd	0.0286	9.71	lag 20	-0.04905	-6.47
wp31	0.003883	0.87	lag 21	-0.04112	-5.43
wp32	0.006726	1.9	lag 22	-0.01032	-1.36
			lag 23	-0.03121	-4.13
			lag24	0.012917	1.71
	Adj R-Sq 0.8374				

Table A.11: NE2 area winter load estimation for step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	744.503	21.25	lag 1	-0.11065	-14.63
trend	-0.00098	-3.95	lag 2	-0.02387	-3.15
ne2load1	0.838	177.61	lag 3	0.039726	5.26
ne2load24	0.4872	65.22	lag 4	0.005856	0.78
ne2load25	-0.4391	-57.38	lag 5	0.022048	2.92
pne21	0.3836	3.77	lag 6	0.015274	2.02
pne224	1.0721	8.69	lag 7	0.00679	0.9
pne225	-0.8348	-6.64	lag 8	0.04179	5.54
c_24hour	-236.071	-51.46	lag 9	0.025262	3.35
s_24hour	-82.816	-12.29	lag 10	-0.0217	-2.87
c_12hour	-169.412	-39.3	lag 11	-0.02744	-3.63
s_12hour	-115.362	-27.34	lag 12	-0.00437	-0.58
c_6hour	24.8416	9.29	lag 13	-0.02608	-3.45
s_6hour	42.9443	15.99	lag 14	-0.03321	-4.4
c_week	15.1974	3.74	lag 15	-0.01278	-1.69
s_week	21.9082	5.44	lag 16	0.001587	0.21
weekend cycle	139.3722	12.95	lag 17	0.033157	4.4
hddc_24hour	0.9982	3.43	lag 18	0.021097	2.8
hdds_24hour	-1.4911	-4.75	lag 19	-0.02514	-3.33
hddc_week	0.1498	0.43	lag 20	-0.00889	-1.18
hdds_week	0.3628	0.5156	lag 21	0.049582	6.57
hddweekendcycle	0.0573	0.06	lag 22	0.071121	9.42
hdd	10.929	11.18	lag 23	-0.09963	-13.16
sq_hdd	-0.1068	-4.51	lag24	0.051599	6.82
wp31	0.0833	2.3			
wp32	-0.0603	-2.34			
	Adj R-Sq 0.9784				

Table A12: NE2 area winter price estimation results for step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-8.3323	-3.5	lag 1	0.042884	5.67
trend	1.15E-05	0.49	lag 2	0.024305	3.21
ne2load1	0.002317	8.87	lag 3	-0.0052	-0.69
ne2load24	0.009932	23.01	lag 4	-0.03111	-4.11
ne2load25	-0.0106	-23.89	lag 5	-0.0096	-1.27
pne21	0.642	105.57	lag 6	-0.03927	-5.18
pne224	0.1461	18.67	lag 7	-0.03452	-4.55
pne225	-0.0631	-8.01	lag 8	-0.0368	-4.85
c_24hour	1.2277	4.87	lag 9	-0.04432	-5.84
s_24hour	-1.0977	-2.82	lag 10	-0.03833	-5.04
c_12hour	0.6273	2.96	lag 11	-0.05169	-6.8
s_12hour	0.1852	0.84	lag 12	-0.01702	-2.24
c_6hour	1.2959	9.48	lag 13	-0.05017	-6.6
s_6hour	0.0362	0.26	lag 14	-0.02366	-3.11
c_week	-0.0534	-0.18	lag 15	-0.02039	-2.68
s_week	-0.2851	-0.96	lag 16	-0.01436	-1.89
weekend cycle	-1.1987	-1.83	lag 17	-0.02085	-2.75
cddc_24hour	-0.0519	-3.74	lag 18	-0.00846	-1.12
cdds_24hour	-0.0459	-2.83	lag 19	-0.01635	-2.16
cddc_week	0.0523	2.2	lag 20	-0.00891	-1.18
cdds_week	0.0265	1.08	lag 21	-0.00071	-0.09
cddweekendcycle	0.1035	1.92	lag 22	3.43E-05	0
cdd	-0.0269	-0.45	lag 23	-0.01404	-1.85
sq_cdd	0.009155	6.02	lag24	0.030577	4.04
wp31	0.0116	3.46			
wp32	-0.00117	-0.49			
	Adj R-Sq 0.7786				

Table A.13: NE2 area summer load estimation results for step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	108.5776	11.07	lag 1	-0.55641	-73.77
trend	-0.00018	-2.2	lag 2	0.157338	18.23
ne2load1	0.9748	488.77	lag 3	-0.04256	-4.89
ne2load24	0.8258	230.29	lag 4	0.049059	5.64
ne2loadc25	-0.8175	-216.38	lag 5	-0.00993	-1.14
c_24hour	-71.2005	-25.65	lag 6	-0.00248	-0.28

s_24hour	13.2244	4.75	lag 7	0.077165	8.86
c_week	14.478	6.89	lag 8	0.057377	6.57
s_week	6.4386	2.96	lag 9	-0.04711	-5.39
weekend cycle	28.3225	4.56	lag 10	-0.01732	-1.99
cddc_24hour	-2.6806	-8.96	lag 11	0.0124	1.42
cdds_24hour	1.7356	4.5	lag 12	0.003646	0.42
cddc_week	-0.6895	-2.6	lag 13	-0.03084	-3.54
cdds_week	0.247	0.87	lag 14	0.027631	3.17
cddweekendcycle	-6.0965	-7.84	lag 15	0.095183	10.93
cdd	7.6041	9.65	lag 16	0.036759	4.21
sq_cdd	0.0333	1.38	lag 17	-0.02437	-2.79
			lag 18	-0.01342	-1.54
			lag 19	0.012508	1.44
			lag 20	-0.0024	-0.28
			lag 21	0.066616	7.66
			lag 22	0.02794	3.21
			lag 23	-0.03752	-4.35
			lag24	0.070999	9.41
	Adj R-Sq 0.9978				

Table A.14: NE2 area summer price estimation results for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-10.1565	-22.68	lag 1	-0.71164	-94.2
trend	4.32E-05	5.33	lag 2	0.26203	28.29
pre_ ne2load	9.54E-05	0.67	lag 3	-0.2397	-25.61
ne2load1	0.003858	25.71	lag 4	0.081488	8.68
ne2load24	0.005619	39.02	lag 5	-0.11697	-12.66
ne2load25	-0.00794	-54.12	lag 6	0.16176	17.65
pne21	0.6716	670.9	lag 7	-0.07373	-7.97
pn2124	0.1002	99.57	lag 8	0.071685	7.74
pne225	-0.0332	-33.29	lag 9	-0.05904	-6.38
c_24hour	-1.4368	-14.01	lag 10	0.070987	7.67
s_24hour	-0.4943	-4.32	lag 11	-0.08487	-9.18
c_week	-0.4527	-5.93	lag 12	0.063369	6.84
s_week	-0.4104	-5.52	lag 13	0.032943	3.56
weekend cycle	-1.8462	-13.11	lag 14	-0.10112	-10.94
wp31	0.006389	4.82	lag 15	-0.01464	-1.58
wp32	0.004476	4.25	lag 16	0.089743	9.71
			lag 17	-0.04789	-5.17
			lag 18	-0.0189	-2.04
			lag 19	0.190917	20.83

			lag 20	-0.23879	-25.85
			lag 21	0.216263	23.03
			lag 22	-0.19337	-20.66
			lag 23	-0.06147	-6.64
			lag24	-0.04253	-5.63
	Adj R-Sq 0.9961				

Table A.15: NE2 area winter load estimation results for step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	682.0625	128.98	lag 1	-0.00376	-0.5
trend	-0.00146	-23.19	lag 2	0.1168	15.43
ne2load1	0.8554	1542.9	lag 3	-0.02519	-3.32
ne2load24	0.4894	448.54	lag 4	-0.08201	-10.8
ne2load25	-0.4428	-395.15	lag 5	0.073106	9.59
c_24hour	-231.279	-375.1	lag 6	0.152785	20.55
s_24hour	-64.1857	-69.93	lag 7	0.194416	26.06
c_12hour	-177.328	-164.85	lag 8	0.197532	25.98
s_12hour	-108.324	-100.36	lag 9	-0.01209	-1.56
c_6hour	28.1284	54.79	lag 10	-0.07302	-9.43
s_6hour	44.1309	85.6	lag 11	-0.08232	-10.64
c_week	15.327	21.97	lag 12	-0.19706	-25.81
s_week	19.5972	28.82	lag 13	-0.18689	-24.48
weekend cycle	122.0266	100.11	lag 14	-0.07879	-10.18
hddc_24hour	0.8567	26.14	lag 15	0.017016	2.2
hdds_24hour	-1.5168	-40.15	lag 16	-0.04217	-5.45
hddc_week	0.1773	3.36	lag 17	-0.00539	-0.71
hdds_week	0.342	6.47	lag 18	-0.1298	-17.4
hddweekendcycle	0.3336	3.23	lag 19	-0.23187	-31.18
hdd	9.888	77.15	lag 20	-0.01339	-1.76
sq_hdd	-0.0912	-26.44	lag 21	-0.04169	-5.49
			lag 22	-0.07461	-9.82
			lag 23	0.000896	0.12
			lag24	-0.01984	-2.62
	Adj R-Sq 0.9993				

Table A.16: NE2 area winter price estimation for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-16.2866	-28.8	lag 1	-0.64823	-85.66

trend	9.50E-07	0.12	lag 2	-0.07754	-8.64
pre_ ne2load	0.003497	19.43	lag 3	0.041713	4.65
ne2load1	-0.00034	-1.98	lag 4	-0.24057	-26.8
ne2load24	0.008894	102.23	lag 5	0.212298	23.28
ne2load25	-0.00913	-104.09	lag 6	-0.08777	-9.52
pne21	0.6106	938.79	lag 7	-0.06307	-6.83
pne224	0.1084	157.26	lag 8	0.174177	18.84
pne225	-0.0315	-47	lag 9	-0.18298	-19.6
c_24hour	2.2672	38.86	lag 10	0.070247	7.45
s_24hour	0.3553	5.3	lag 11	-0.06195	-6.57
c_12hour	1.0391	22.12	lag 12	0.125102	13.27
s_12hour	0.7448	16.43	lag 13	-0.08696	-9.23
c_6hour	1.2496	81.47	lag 14	-0.03257	-3.45
s_6hour	-0.0676	-4.11	lag 15	0.067086	7.12
c_week	0.3865	5.47	lag 16	-0.00975	-1.04
s_week	-0.2404	-3.42	lag 17	-0.00445	-0.48
weekend cycle	-1.2205	-8.81	lag 18	0.074209	8.04
wp31	0.0101	9.28	lag 19	-0.10719	-11.62
wp32	0.001065	1.36	lag 20	0.114363	12.54
			lag 21	0.040678	4.53
			lag 22	-0.06292	-7.01
			lag 23	-0.12432	-13.86
			lag24	0.024203	3.2
	Adj R-Sq 0.9978				

Table A.17: Boston summer load estimation results for step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	65.5935	11.23	lag 1	-0.98154	-129.84
trend	5.65E-05	0.95	lag 2	0.43568	41.12
Bostonload1	0.9344	322.2	lag 3	-0.13717	-12.36
Bostonload24	0.7654	156.27	lag 4	0.026863	2.41
Bostonload25	-0.7323	-142.35	lag 5	0.043278	3.88
pBoston1	0.00227	0.15	lag 6	-0.04415	-3.96
pBoston24	-0.0569	-3.73	lag 7	0.05547	4.97
pBoston25	-0.0602	-3.91	lag 8	0.038759	3.47
c_24hour	-34.8703	-24.03	lag 9	-0.02337	-2.09
s_24hour	-0.1299	-0.09	lag 10	-0.05894	-5.28
c_week	8.3063	7.1	lag 11	0.042739	3.83
s_week	2.8457	2.4	lag 12	0.052442	4.7
weekend cycle	25.1842	7.48	lag 13	-0.05949	-5.33
cddc_24hour	-0.9563	-6.19	lag 14	0.035562	3.19

cdds_24hour	0.846	4.69	lag 15	0.036466	3.27
cddc_week	-0.1377	-0.92	lag 16	0.048494	4.35
cdds_week	0.2935	1.85	lag 17	-0.03339	-2.99
cddweekendcycle	-0.8633	-2.05	lag 18	-0.0055	-0.49
cdd	3.091	7.35	lag 19	0.001763	0.16
sq_cdd	-0.011	-0.91	lag 20	0.01992	1.79
wp31	0.04	2.68	lag 21	0.025523	2.29
wp32	-0.0258	-2.19	lag 22	-0.00131	-0.12
			lag 23	-0.00664	-0.63
			lag24	0.025712	3.4
	Adj R-Sq 0.9974				

Table A.18: Boston summer price estimation results for step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-11.671	-7.6	lag 1	0.035035	4.63
trend	5.23E-05	2.31	lag 2	0.067505	8.93
Bostonload1	0.007923	13.05	lag 3	-0.05491	-7.25
Bostonload24	0.0161	14.16	lag 4	-0.06772	-8.93
Bostonload25	-0.0196	-16.28	lag 5	-0.05473	-7.2
pBoston1	0.678	119.63	lag 6	-0.01113	-1.46
pBoston24	0.1151	15.2	lag 7	-0.01124	-1.48
pBoston25	-0.0508	-6.65	lag 8	-0.02615	-3.44
c_24hour	-0.1033	-0.37	lag 9	-0.00602	-0.79
s_24hour	-0.7803	-2.57	lag 10	-0.0171	-2.25
c_week	0.2272	0.76	lag 11	-0.02521	-3.32
s_week	-0.8923	-2.95	lag 12	-0.0129	-1.7
weekend cycle	-0.1276	-0.2	lag 13	0.003181	0.42
cddc_24hour	-0.2507	-8.82	lag 14	-0.01589	-2.09
cdds_24hour	0.1035	2.86	lag 15	-0.00473	-0.62
cddc_week	-0.0613	-1.76	lag 16	0.012453	1.64
cdds_week	0.132	3.66	lag 17	-0.00825	-1.09
cddweekendcycle	-0.2053	-2.4	lag 18	-0.03133	-4.12
cdd	-0.0452	-0.5	lag 19	-0.02525	-3.32
sq_cdd	0.0158	5.1	lag 20	-0.04016	-5.29
wp31	0.003077	0.67	lag 21	-0.0327	-4.31
wp32	0.006972	1.93	lag 22	-0.02278	-3.01
			lag 23	-0.03259	-4.31
			lag24	0.011667	1.54
	Adj R-Sq 0.8171				

Table A.19: Boston winter load estimation for step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	347.0946	24.84	lag 1	0.044077	5.82
trend	-3.1E-05	-0.31	lag 2	-0.06605	-8.79
Bostonload1	0.7817	161.82	lag 3	-0.028	-3.72
Bostonload24	0.2985	40.63	lag 4	-0.03173	-4.22
Bostonload25	-0.2305	-30.96	lag 5	-0.02319	-3.08
pBoston1	0.2882	7.76	lag 6	-0.0059	-0.78
pBoston24	0.5536	11.61	lag 7	0.024881	3.31
pBoston25	-0.4761	-9.82	lag 8	0.035799	4.76
c_24hour	-104.759	-61.32	lag 9	-0.00399	-0.53
s_24hour	-29.8324	-11.95	lag 10	-0.04278	-5.69
c_12hour	-66.2256	-50.63	lag 11	-0.01611	-2.14
s_12hour	-46.472	-34.35	lag 12	0.031993	4.25
c_6hour	5.5663	6.66	lag 13	0.009947	1.32
s_6hour	15.7097	18.7	lag 14	-0.02189	-2.91
c_week	6.72	4.35	lag 15	-0.01346	-1.79
s_week	11.3254	7.54	lag 16	0.011664	1.55
weekend cycle	60.6591	15.55	lag 17	0.031757	4.22
hddc_24hour	0.5876	4.53	lag 18	0.017454	2.32
hdds_24hour	-0.4976	-3.62	lag 19	-0.02221	-2.95
hddc_week	0.009278	0.06	lag 20	-0.0023	-0.31
hdds_week	-0.0855	-0.54	lag 21	0.053848	7.16
hddweekendcycle	0.5246	1.34	lag 22	0.05019	6.67
hdd	4.177	9.87	lag 23	-0.12421	-16.52
sq_hdd	-0.0414	-3.65	lag24	0.004708	0.62
wp31	0.0236	1.6			
wp32	-0.0165	-1.57			
	Adj R-Sq 0.9703				

Table A.20: Boston winter price estimation results for step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-1.8142	-0.76	lag 1	0.051712	6.84
trend	1.74E-05	0.73	lag 2	0.036071	4.76
Bostonload1	0.001877	2.7	lag 3	-0.00642	-0.85
Bostonload24	0.0171	15.09	lag 4	-0.03287	-4.34
Bostonload25	-0.0173	-15.05	lag 5	-0.0092	-1.21
pBoston1	0.6622	111.08	lag 6	-0.04514	-5.95
pBoston24	0.1685	21.72	lag 7	-0.03377	-4.45

pBoston25	-0.085	-10.84	lag 8	-0.04291	-5.65
c_24hour	-0.4921	-2.11	lag 9	-0.04736	-6.24
s_24hour	-1.7438	-4.82	lag 10	-0.0429	-5.64
c_12hour	-0.8454	-4.69	lag 11	-0.04673	-6.14
s_12hour	-0.7746	-4.04	lag 12	-0.00816	-1.07
c_6hour	1.5859	12.02	lag 13	-0.04596	-6.04
s_6hour	0.3708	2.8	lag 14	-0.02353	-3.09
c_week	0.1075	0.37	lag 15	-0.02487	-3.27
s_week	-0.0146	-0.05	lag 16	-0.02303	-3.03
weekend cycle	0.0173	0.03	lag 17	-0.02944	-3.88
hddc_24hour	-0.0243	-1.63	lag 18	-0.01177	-1.55
hdds_24hour	-0.0244	-1.44	lag 19	-0.01685	-2.22
hddc_week	0.0399	1.44	lag 20	-0.00737	-0.97
hdds_week	0.0244	0.88	lag 21	0.000203	0.03
hddweekendcycle	0.0507	0.82	lag 22	0.002371	0.31
hdd	0.1277	1.87	lag 23	-0.0228	-3.01
sq_hdd	0.007804	4.14	lag24	0.032358	4.28
wp31	0.0107	3.16			
wp32	-0.00074	-0.31			
	Adj R-Sq 0.7673				

Table A.21: Boston summer load estimation results for step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	53.1664	14.35	lag 1	-0.57071	-75.63
trend	-4.16E-06	-0.14	lag 2	0.064311	7.4
Bostonload1	0.9767	491.84	lag 3	-0.01571	-1.81
Bostonload24	0.7745	198.08	lag 4	0.042636	4.91
Bostonload25	-0.7717	-190.94	lag 5	-0.00985	-1.13
c_24hour	-29.3237	-28.44	lag 6	0.028243	3.25
s_24hour	6.3413	5.99	lag 7	0.074754	8.6
c_week	3.5978	4.84	lag 8	0.022609	2.59
s_week	2.4925	3.28	lag 9	-0.08524	-9.78
weekend cycle	3.8206	1.73	lag 10	-0.00903	-1.04
cddc_24hour	-1.3283	-11.94	lag 11	0.0674	7.75
cdds_24hour	0.4978	3.85	lag 12	-0.00053	-0.06
cddc_week	-0.2568	-2.57	lag 13	-0.02459	-2.82
cdds_week	0.2508	2.37	lag 14	0.062415	7.18
cddweekendcycle	-1.614	-5.59	lag 15	0.095899	11.01
cdd	2.6812	9.1	lag 16	-0.01272	-1.46
sq_cdd	-0.0184	-2.06	lag 17	-0.01973	-2.26
			lag 18	-0.00053	-0.06

			lag 19	0.030203	3.47
			lag 20	0.019819	2.28
			lag 21	0.038963	4.48
			lag 22	0.029911	3.44
			lag 23	-0.04776	-5.5
			lag24	0.062609	8.3
	Adj R-Sq 0.9976				

Table A.22: Boston summer price estimation results for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-10.6832	-25.41	lag 1	-0.77499	-102.51
trend	0.0000579	7.9	lag 2	0.391571	40.98
pre_Bostonload	-0.000502	-1.25	lag 3	-0.25094	-25.31
Bostonload1	0.009792	23.17	lag 4	-0.00031	-0.03
Bostonload24	0.0162	39.9	lag 5	-0.09699	-9.79
Bostonload25	-0.0211	-50.77	lag 6	0.161818	16.29
pBoston1	0.6841	738.67	lag 7	-0.15822	-15.87
pBoston24	0.1028	109.85	lag 8	0.119679	12.02
pBoston25	-0.0412	-44.04	lag 9	0.000633	0.06
c_24hour	-1.4009	-16.88	lag 10	0.053654	5.41
s_24hour	-0.5254	-5.72	lag 11	-0.1283	-12.95
c_week	-0.2483	-3.18	lag 12	0.158089	15.89
s_week	-0.3745	-4.89	lag 13	-0.0507	-5.1
weekend cycle	-1.5805	-10.27	lag 14	-0.07528	-7.6
wp31	0.005774	4.26	lag 15	-0.06171	-6.22
wp32	0.004765	4.43	lag 16	0.156102	15.72
			lag 17	-0.17419	-17.49
			lag 18	0.112676	11.3
			lag 19	0.029488	2.97
			lag 20	-0.12912	-13.03
			lag 21	0.2211	22.21
			lag 22	-0.175	-17.65
			lag 23	-0.05592	-5.85
			lag24	-0.01444	-1.91
	Adj R-Sq 0.9960				

Table A.23: Boston winter load estimation results for step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value

Intercept	289.8791	123.39	lag 1	0.124839	16.5
trend	-0.000292	-7.06	lag 2	0.195879	26.25
Bostonload1	0.8112	1318.29	lag 3	0.125049	16.48
Bostonload24	0.3108	252.43	lag 4	-0.09338	-12.74
Bostonload25	-0.2412	-192.7	lag 5	-0.06024	-8.29
c_24hour	-100.2841	-385.7	lag 6	0.006059	0.83
s_24hour	-18.6595	-50.29	lag 7	0.031948	4.4
c_12hour	-69.6325	-343.71	lag 8	-0.00337	-0.46
s_12hour	-42.1411	-195.4	lag 9	-0.08932	-12.29
c_6hour	7.1334	50.81	lag 10	-0.07394	-10.14
s_6hour	16.3115	115.32	lag 11	-0.014	-1.92
c_week	8.6543	31.39	lag 12	-0.04534	-6.27
s_week	9.5173	35.88	lag 13	-0.11313	-15.65
weekend cycle	55.5491	123.25	lag 14	-0.0981	-13.48
hddc_24hour	0.4926	29.47	lag 15	-0.01968	-2.7
hdds_24hour	-0.5227	-28.82	lag 16	0.005732	0.79
hddc_week	-0.0213	-0.86	lag 17	0.030442	4.19
hdds_week	-0.034	-1.41	lag 18	0.013283	1.83
hddweekendcycle	0.429	9.21	lag 19	-0.05645	-7.77
hdd	3.9858	67.92	lag 20	-0.15904	-21.9
sq_hdd	-0.0341	-20.06	lag 21	-0.28788	-39.28
			lag 22	0.072917	9.61
			lag 23	-0.2084	-27.93
			lag24	-0.01289	-1.7
	Adj R-Sq 0.9989				

Table A.24: Boston winter price estimation for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-17.0698	-29.04	lag 1	-0.57979	-76.65
trend	-1.14E-07	-0.02	lag 2	-0.06516	-7.52
pre_Bostonload	0.0193	38.05	lag 3	-0.02613	-3.02
Bostonload1	-0.011	-26.79	lag 4	-0.2078	-23.99
Bostonload24	0.0135	82.33	lag 5	0.126267	14.35
Bostonload25	-0.0134	-92.06	lag 6	0.005074	0.57
pBoston1	0.6127	820.68	lag 7	-0.05362	-6.06
pBoston24	0.1168	146.39	lag 8	0.096965	10.96
pBoston25	-0.0386	-49.95	lag 9	-0.13073	-14.72
c_24hour	2.0472	29.18	lag 10	-0.02601	-2.91
s_24hour	0.5	7.23	lag 11	0.049245	5.52
c_12hour	0.1479	3.23	lag 12	0.091243	10.29
s_12hour	0.5054	10.94	lag 13	-0.13224	-14.91

c_6hour	1.5697	115.28	lag 14	0.070236	7.87
s_6hour	0.1367	8.65	lag 15	0.01924	2.15
c_week	0.4119	5.84	lag 16	0.018652	2.1
s_week	-0.2161	-3.08	lag 17	-0.00931	-1.05
weekend cycle	-1.3688	-9.29	lag 18	0.027528	3.11
wp31	0.009928	9.63	lag 19	-0.03812	-4.31
wp32	0.001117	1.51	lag 20	0.042155	4.79
			lag 21	-0.02412	-2.79
			lag 22	0.064828	7.49
			lag 23	-0.16061	-18.55
			lag24	0.028068	3.71
	Adj R-Sq 0.9971				

Table A.25: NY1 area summer load estimation results for step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	178.9237	12.64	lag 1	-0.44849	-59.4
trend	-0.00046	-4.11	lag 2	0.029484	3.56
ny1load1	0.9296	266.09	lag 3	0.028371	3.43
ny1load24	0.8316	153.26	lag 4	-0.00295	-0.36
ny1load25	-0.7981	-135.45	lag 5	0.010662	1.29
pny11	0.48	3.41	lag 6	-0.01934	-2.34
pny124	0.4483	2.91	lag 7	0.001649	0.2
pny125	-0.7747	-4.39	lag 8	0.045004	5.44
c_24hour	-39.664	-16.66	lag 9	0.016419	1.98
s_24hour	-7.0308	-2.86	lag 10	-0.0174	-2.1
c_week	14.8571	7.05	lag 11	-0.00011	-0.01
s_week	7.9259	3.68	lag 12	0.017139	2.07
weekend cycle	46.2688	7.78	lag 13	-0.01398	-1.69
cddc_24hour	0.4984	1.43	lag 14	-0.00096	-0.12
cdds_24hour	2.7168	7.09	lag 15	0.010912	1.32
cddc_week	-0.8113	-2.63	lag 16	0.064947	7.85
cdds_week	0.4159	1.3	lag 17	0.016995	2.05
cddweekendcycle	-4.3523	-4.95	lag 18	-0.00491	-0.59
cdd	6.9249	8.12	lag 19	0.004502	0.54
sq_cdd	0.1161	3.93	lag 20	0.00557	0.67
wp31	-0.00117	-0.04	lag 21	0.020675	2.5
wp32	0.000169	0.01	lag 22	0.01045	1.26
			lag 23	-0.02726	-3.29
			lag24	0.057338	7.59
	Adj R-Sq 0.9922				

Table A.26: NY1 area summer price estimation results for step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-2.1772	-5.57	lag 1	0.069129	9.18
trend	8.56E-06	2.37	lag 2	-0.03021	-4.02
ny1load1	0.000711	8.01	lag 3	-0.05386	-7.16
ny1load24	0.002842	19.34	lag 4	-0.03708	-4.92
ny1load25	-0.00321	-19.98	lag 5	-0.04984	-6.61
pny11	0.8658	219.82	lag 6	-0.00184	-0.24
pny124	0.6153	100.38	lag 7	-0.01897	-2.51
pny125	-0.5242	-79.06	lag 8	0.028614	3.79
c_24hour	-0.3049	-4.98	lag 9	-0.00994	-1.32
s_24hour	-0.0225	-0.35	lag 10	-0.01569	-2.08
c_week	0.2997	5.07	lag 11	-0.01452	-1.92
s_week	-0.097	-1.6	lag 12	0.023809	3.15
weekend cycle	0.6553	4.4	lag 13	-0.00175	-0.23
cddc_24hour	-0.0353	-4.04	lag 14	0.007112	0.94
cdds_24hour	0.0446	4.57	lag 15	0.016935	2.24
cddc_week	-0.0192	-2.33	lag 16	0.023954	3.17
cdds_week	0.015	1.78	lag 17	-0.00338	-0.45
cddweekendcycle	-0.0712	-3.22	lag 18	0.017611	2.33
cdd	0.0408	1.88	lag 19	0.006334	0.84
sq_cdd	0.003229	4.03	lag 20	-0.01846	-2.45
wp31	-0.00147	-1.76	lag 21	-0.02757	-3.66
wp32	0.002178	3.28	lag 22	-0.00647	-0.86
			lag 23	-0.07767	-10.32
			lag24	0.096744	12.85
	Adj R-Sq 0.9757				

Table A.27: NY1 area winter load estimation for step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	232.9388	10.46	lag 1	-0.23813	-31.33
trend	-0.0005	-3.32	lag 2	0.024439	3.13
ny1load1	0.9388	205.55	lag 3	0.030713	3.93
ny1load24	0.678	71.09	lag 4	-9.7E-05	-0.01
ny1load25	-0.6609	-67.64	lag 5	0.009361	1.2
pny11	-0.3108	-1.99	lag 6	0.00053	0.07
pny124	1.3443	6.94	lag 7	0.009778	1.25
pny125	-0.9713	-4.41	lag 8	0.03039	3.89

c_24hour	-76.5	-26.3	lag 9	0.030039	3.85
s_24hour	-3.0804	-0.92	lag 10	-0.00253	-0.32
c_12hour	-63.4319	-23.64	lag 11	-0.01689	-2.16
s_12hour	-38.6917	-16.92	lag 12	-0.00072	-0.09
c_6hour	7.044	4.22	lag 13	-0.01373	-1.76
s_6hour	18.3068	10.71	lag 14	-0.00763	-0.98
c_week	10.489	4.05	lag 15	0.006691	0.86
s_week	4.121	1.61	lag 16	0.011563	1.48
weekend cycle	38.0874	5.46	lag 17	0.04181	5.36
hddc_24hour	0.6318	3.64	lag 18	0.008133	1.04
hdds_24hour	-0.633	-3.57	lag 19	-0.00976	-1.25
hddc_week	-0.2177	-1.14	lag 20	-0.01165	-1.49
hdds_week	0.2914	1.43	lag 21	0.021035	2.69
hddweekendcycle	-0.3476	-0.7	lag 22	0.043557	5.58
hdd	3.3626	5.95	lag 23	0.005863	0.75
sq_hdd	-0.0406	-3.32	lag24	-0.01784	-2.35
wp31	0.0257	1.21			
wp32	-0.0145	-0.95			
	Adj R-Sq 0.9820				

Table A.28: NY1 area winter price estimation results for step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	2.2991	3.53	lag 1	-0.00868	-1.15
trend	-1.4E-05	-2.71	lag 2	-0.0107	-1.42
ny1load1	0.000994	8.17	lag 3	0.020239	2.68
ny1load24	0.003094	11.98	lag 4	0.040502	5.37
ny1load25	-0.0044	-16.5	lag 5	0.029986	3.97
pny11	0.8254	184.82	lag 6	0.008619	1.14
pny124	0.7139	123.54	lag 7	-0.00378	-0.5
pny125	-0.5715	-85.69	lag 8	-0.01902	-2.52
c_24hour	-0.1521	-2.27	lag 9	-0.03174	-4.2
s_24hour	-0.4438	-5.34	lag 10	-0.0638	-8.45
c_12hour	-0.2725	-3.6	lag 11	-0.08774	-11.6
s_12hour	-0.152	-2.25	lag 12	-0.07303	-9.62
c_6hour	0.5082	12.02	lag 13	-0.02827	-3.73
s_6hour	0.042	0.97	lag 14	-0.04295	-5.68
c_week	0.0692	0.86	lag 15	-0.01518	-2.01
s_week	-0.0905	-1.12	lag 16	0.004922	0.65
weekend cycle	0.4491	2.19	lag 17	-0.00773	-1.02
hddc_24hour	-0.00461	-1.43	lag 18	0.011098	1.47
hdds_24hour	-0.0203	-5.94	lag 19	0.026846	3.56

hddc_week	0.0124	2.12	lag 20	0.025849	3.42
hdds_week			lag 21	0.025606	3.39
hddweekendcycle			lag 22	0.040134	5.32
hdd			lag 23	-0.06071	-8.04
sq_hdd			lag24	0.099325	13.13
wp31					
wp32					
	Adj R-Sq 0.9623				

Table A.29: NY1 area summer load estimation results for step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	135.5151	30.2	lag 1	-0.58795	-77.83
trend	-0.00037	-12.04	lag 2	0.16346	18.66
ny1load1	0.9689	768.24	lag 3	-0.0022	-0.25
ny1load24	0.8351	435.83	lag 4	-0.0291	-3.29
ny1loadc25	-0.8278	-394.58	lag 5	-0.05975	-6.75
c_24hour	-36.8732	-42.23	lag 6	0.030378	3.43
s_24hour	0.0994	0.11	lag 7	0.073626	8.31
c_week	7.6433	9.94	lag 8	0.003001	0.34
s_week	6.7092	8.58	lag 9	-0.02532	-2.85
weekend cycle	11.9506	5.13	lag 10	0.019601	2.22
cddc_24hour	-0.1954	-1.52	lag 11	-0.00073	-0.08
cdds_24hour	2.2293	15.95	lag 12	-0.02868	-3.25
cddc_week	-1.0526	-9.3	lag 13	-0.04482	-5.08
cdds_week	0.6096	5.18	lag 14	0.064047	7.26
cddweekendcycle	-5.9334	-17.77	lag 15	0.115214	13.04
cdd	6.7995	21.25	lag 16	0.002664	0.3
sq_cdd	0.0914	8.63	lag 17	0.023001	2.59
			lag 18	0.027249	3.08
			lag 19	-0.02243	-2.53
			lag 20	0.027063	3.06
			lag 21	0.003353	0.38
			lag 22	0.018652	2.11
			lag 23	0.035416	4.04
			lag24	0.045312	6
	Adj R-Sq 0.9990				

Table A.30: NY1 area summer price estimation results for step 2

Variable	NYC winter electricity price	Variable	Residual

	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-2.7997	-52.38	lag 1	-0.0666	-8.81
trend	9.66E-06	20.3	lag 2	-0.21573	-29.63
pre_ ny1load	0.000485	5.29	lag 3	-0.01313	-1.79
ny1load1	0.000404	4.5	lag 4	0.099866	13.65
ny1load24	0.002579	32.5	lag 5	0.10081	13.71
ny1load25	-0.00297	-37.85	lag 6	-0.00867	-1.17
pny11	0.8754	1527.93	lag 7	-0.04307	-5.86
pny124	0.5603	602.31	lag 8	0.091091	12.38
pny125	-0.4792	-483.67	lag 9	0.146907	19.89
c_24hour	-0.5511	-35.9	lag 10	-0.01032	-1.38
s_24hour	0.2244	15.26	lag 11	-0.00227	-0.3
c_week	0.2304	32.68	lag 12	0.051302	6.91
s_week	-0.0769	-11.56	lag 13	0.106629	14.37
weekend cycle	0.2858	16.38	lag 14	0.007989	1.07
wp31	0.001214	11.26	lag 15	0.041357	5.54
wp32	0.001976	22.98	lag 16	-0.008	-1.08
			lag 17	-0.00392	-0.53
			lag 18	-0.09113	-12.4
			lag 19	0.053779	7.29
			lag 20	-0.01983	-2.7
			lag 21	-0.00796	-1.09
			lag 22	0.194396	26.58
			lag 23	-0.27818	-38.21
			lag24	0.007897	1.04
		Adj R-Sq 0.9994			

Table A.31: NY1 area winter load estimation results for step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	205.0891	58.19	lag 1	-0.51663	-67.98
trend	-0.00057	-30.94	lag 2	0.262748	30.74
ny1load1	0.9493	1246.35	lag 3	-0.0349	-3.98
ny1load24	0.7119	539.52	lag 4	0.008312	0.95
ny1loadc25	-0.6965	-499.75	lag 5	-0.0154	-1.76
c_24hour	-69.2826	-155.7	lag 6	0.018164	2.08
s_24hour	1.5579	2.92	lag 7	0.074206	8.49
c_12hour	-62.2667	-115.61	lag 8	0.079571	9.09
s_12hour	-32.7216	-65.76	lag 9	-0.02582	-2.97
c_6hour	8.9812	19.77	lag 10	-0.0262	-3.01
s_6hour	17.4195	38.05	lag 11	-0.02972	-3.41

c_week	7.6035	16.48	lag 12	-0.06578	-7.56
s_week	4.4619	9.75	lag 13	-0.06868	-7.9
weekend cycle	20.3859	15.46	lag 14	-0.00937	-1.08
hddc_24hour	0.5768	22.01	lag 15	0.011478	1.32
hdds_24hour	-0.5771	-21.49	lag 16	0.145689	16.74
hddc_week	-0.1176	-3.48	lag 17	-0.00816	-0.93
hdds_week	0.2445	6.71	lag 18	-0.02722	-3.12
hddweekendcycle	-0.0123	-0.13	lag 19	-0.04321	-4.95
hdd	2.6515	26.36	lag 20	0.023713	2.71
sq_hdd	-0.0402	-19.48	lag 21	0.106258	12.15
			lag 22	0.006968	0.79
			lag 23	0.044843	5.25
			lag24	0.014627	1.92
	Adj R-Sq 0.9995				

Table A.32: NY1 area winter price estimation for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-0.0729	-0.45	lag 1	-0.31439	-41.46
trend	-0.00001	-6.12	lag 2	-0.39452	-50.3
pre_ ny1load	0.000403	2.45	lag 3	-0.05491	-6.56
ny1load1	0.000768	4.67	lag 4	0.080983	9.66
ny1load24	0.003735	31.49	lag 5	0.030151	3.59
ny1load25	-0.00479	-40.55	lag 6	0.052234	6.22
pny11	0.8624	907.56	lag 7	0.232914	27.69
pny124	0.6667	796.55	lag 8	0.008268	0.96
pny125	-0.5684	-536.91	lag 9	-0.14768	-17.21
c_24hour	0.0463	2.46	lag 10	0.045821	5.3
s_24hour	-0.3314	-16.34	lag 11	-0.13815	-16.04
c_12hour	-0.2854	-13.5	lag 12	-0.10681	-12.37
s_12hour	0.003431	0.18	lag 13	0.108746	12.59
c_6hour	0.601	109.4	lag 14	0.110391	12.82
s_6hour	0.0211	3.38	lag 15	-0.04295	-4.97
c_week	0.1229	6.58	lag 16	-0.06747	-7.86
s_week	-0.0442	-2.46	lag 17	0.013636	1.59
weekend cycle	0.4078	9.77	lag 18	0.01968	2.34
wp31	0.00016	0.68	lag 19	-0.03431	-4.08
wp32	0.000996	5.81	lag 20	-0.01101	-1.31
			lag 21	0.011595	1.38
			lag 22	0.084105	10.05
			lag 23	-0.17169	-21.89
			lag24	0.066506	8.77

	Adj R-Sq 0.9991				

Table A.33: NY2 area summer load estimation results for step 1

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	36.9625	3.77	lag 1	-0.56808	-75.16
trend	9.45E-06	0.07	lag 2	0.046653	5.37
ny2load1	0.9652	364.61	lag 3	0.033131	3.81
ny2load24	0.8538	158.81	lag 4	0.010952	1.26
ny2load25	-0.8282	-146.73	lag 5	0.020191	2.32
pny21	0.1939	1.64	lag 6	0.008953	1.03
pny224	0.0405	0.3	lag 7	0.033552	3.86
pny225	-0.4447	-2.99	lag 8	0.054738	6.29
c_24hour	-49.9568	-17.46	lag 9	-0.00878	-1.01
s_24hour	-0.6461	-0.23	lag 10	-0.02952	-3.39
c_week	13.0827	5.8	lag 11	-0.00581	-0.67
s_week	2.7654	1.17	lag 12	0.01399	1.61
weekend cycle	19.4934	3.06	lag 13	-0.01314	-1.51
cddc_24hour	-0.8332	-2.97	lag 14	0.006572	0.75
cdds_24hour	1.4362	4.24	lag 15	0.032337	3.71
cddc_week	-0.4769	-1.73	lag 16	0.047125	5.41
cdds_week	-0.5358	-1.76	lag 17	-0.00736	-0.84
cddweekendcycle	-1.6056	-2.06	lag 18	-0.01412	-1.62
cdd	1.0228	1.3	lag 19	-0.01048	-1.2
sq_cdd	0.1234	4.43	lag 20	0.005595	0.64
wp31	0.0337	1.05	lag 21	0.006066	0.7
wp32	-0.0156	-0.61	lag 22	0.023769	2.73
			lag 23	0.008789	1.01
			lag24	0.035787	4.73
	Adj R-Sq 0.9963				

Table A.34: NY2 area summer price estimation results for step 1

Variable	NYC summer electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-1.2165	-3.96	lag 1	-0.09926	-13.2
trend	5.41E-06	1.4	lag 2	-0.03318	-4.42
ny2load1	0.0008	9.6	lag 3	-0.01821	-2.42
ny2load24	0.004412	22.78	lag 4	0.027085	3.6
ny2load25	-0.00504	-25.04	lag 5	0.057602	7.66
pny21	0.8742	232.42	lag 6	0.02312	3.07

pny224	0.5803	92.19	lag 7	0.020595	2.74
pny225	-0.4982	-74.02	lag 8	-0.00807	-1.07
c_24hour	-0.5027	-5.08	lag 9	-0.02171	-2.89
s_24hour	-0.5015	-5.35	lag 10	-0.00984	-1.31
c_week	0.1537	2.23	lag 11	0.025424	3.38
s_week	-0.0603	-0.84	lag 12	0.041638	5.54
weekend cycle	0.4891	2.6	lag 13	0.022797	3.03
cddc_24hour	-0.1006	-8.68	lag 14	0.018304	2.43
cdds_24hour	0.0574	4.26	lag 15	0.017456	2.32
cddc_week	0.0125	1.21	lag 16	0.033471	4.45
cdds_week	0.001962	0.18	lag 17	-0.00972	-1.29
cddweekendcycle	0.0427	1.51	lag 18	0.049849	6.63
cdd	-0.147	-4.96	lag 19	0.014936	1.98
sq_cdd	0.00815	7.66	lag 20	0.011159	1.48
wp31	-0.00019	-0.2	lag 21	9.32E-05	0.01
wp32	0.002039	2.71	lag 22	-0.0081	-1.08
			lag 23	-0.10862	-14.46
			lag24	0.110391	14.69
	Adj R-Sq 0.9833				

Table A.35: NY2 area winter load estimation for step 1

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	159.8308	8.51	lag 1	-0.35426	-46.61
trend	-3.5E-05	-0.27	lag 2	0.05195	6.44
ny2load1	0.9441	229.07	lag 3	0.053935	6.69
ny2load24	0.7394	90.43	lag 4	0.019747	2.45
ny2load25	-0.7178	-85.62	lag 5	0.017976	2.23
pny21	-0.005	-0.04	lag 6	0.034192	4.24
pny224	1.4039	8.65	lag 7	0.042644	5.28
pny225	-1.1678	-6.68	lag 8	0.044247	5.48
c_24hour	-70.3128	-27.67	lag 9	0.008932	1.11
s_24hour	-13.5693	-4.26	lag 10	-0.01403	-1.74
c_12hour	-60.3016	-21.26	lag 11	-0.03203	-3.96
s_12hour	-34.1476	-13.64	lag 12	-0.00762	-0.94
c_6hour	4.7037	2.96	lag 13	-0.01371	-1.7
s_6hour	10.3016	6.47	lag 14	-0.00343	-0.42
c_week	6.2918	3.12	lag 15	0.010664	1.32
s_week	2.9018	1.45	lag 16	0.013195	1.63
weekend cycle	25.5846	4.65	lag 17	0.047091	5.83
hddc_24hour	0.4554	2.69	lag 18	-0.00656	-0.81
hdds_24hour	-0.7745	-4.26	lag 19	-0.0169	-2.09

hddc_week	0.206	1.12	lag 20	-0.002	-0.25
hdds_week	0.0164	0.08	lag 21	0.025187	3.12
hddweekendcycle	0.2368	0.5	lag 22	0.051537	6.39
hdd	0.9927	2.02	lag 23	0.012333	1.53
sq_hdd	0.001589	0.12	lag24	-0.00969	-1.27
wp31	0.00238	0.12			
wp32	-0.0051	-0.38			
	Adj R-Sq 0.9873				

Table A.36: NY2 area winter price estimation results for step 1

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-0.0425	-0.06	lag 1	-0.02573	-3.41
trend	-7.99E-06	-1.28	lag 2	0.016979	2.26
ny2load1	0.00099	7.02	lag 3	0.008823	1.17
ny2load24	0.006815	23.63	lag 4	0.029477	3.92
ny2load25	-0.00776	-25.99	lag 5	0.017734	2.36
pny21	0.8327	181.34	lag 6	0.032676	4.35
pny224	0.629	96.11	lag 7	-0.00677	-0.9
pny225	-0.5017	-69.58	lag 8	-0.02122	-2.82
c_24hour	0.3587	4.51	lag 9	-0.04815	-6.41
s_24hour	-0.5175	-4.5	lag 10	-0.03747	-4.98
c_12hour	-0.051	-0.58	lag 11	-0.07036	-9.35
s_12hour	0.0613	0.76	lag 12	-0.0421	-5.59
c_6hour	0.7609	16.33	lag 13	-0.03867	-5.13
s_6hour	-0.0459	-0.99	lag 14	-0.03294	-4.38
c_week	0.2034	2.4	lag 15	-0.01958	-2.6
s_week	-0.0561	-0.66	lag 16	-0.02727	-3.63
weekend cycle	0.6507	3.16	lag 17	-0.04293	-5.71
hddc_24hour	-0.0292	-5.96	lag 18	0.013125	1.74
hdds_24hour	-0.0342	-5.9	lag 19	0.03793	5.04
hddc_week	0.0151	2.03	lag 20	0.017819	2.37
hdds_week	0.0235	2.97	lag 21	0.02124	2.82
hddweekendcycle	0.0424	2.36	lag 22	0.010708	1.42
hdd	-0.00447	-0.23	lag 23	-0.09461	-12.58
sq_hdd	0.001496	2.95	lag24	0.112349	14.87
wp31	0.001659	1.81			
wp32	8.18E-05	0.13			
	Adj R-Sq 0.9737				

Table A.37: NY2 area summer load estimation results for step 2

Variable	NYC summer load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	56.9419	16.3	lag 1	-0.71138	-94.13
trend	-6.4E-05	-1.53	lag 2	0.204015	21.99
ny2load1	0.9788	959.2	lag 3	0.018265	1.94
ny2load24	0.8467	342.88	lag 4	-0.00584	-0.62
ny2loadc25	-0.8362	-327.64	lag 5	0.016526	1.76
c_24hour	-48.465	-36.06	lag 6	0.101559	10.82
s_24hour	3.1194	2.64	lag 7	0.044686	4.74
c_week	8.6665	9.2	lag 8	-0.00114	-0.12
s_week	4.1133	4.17	lag 9	-0.04062	-4.31
weekend cycle	7.0942	2.58	lag 10	-0.0032	-0.34
cddc_24hour	-1.6758	-13.54	lag 11	0.00341	0.36
cdds_24hour	1.5379	10.31	lag 12	0.00121	0.13
cddc_week	-0.4137	-3.49	lag 13	0.000535	0.06
cdds_week	-0.4794	-3.65	lag 14	0.073618	7.82
cddweekendcycle	-2.2607	-6.64	lag 15	0.033006	3.5
cdd	2.133	6.26	lag 16	0.001229	0.13
sq_cdd	0.0961	8.08	lag 17	-0.01493	-1.58
			lag 18	-0.00699	-0.74
			lag 19	0.001989	0.21
			lag 20	0.017861	1.9
			lag 21	0.070191	7.48
			lag 22	0.004681	0.5
			lag 23	0.008028	0.87
			lag24	0.035557	4.71
	Adj R-Sq 0.9992				

Table A.38: NY2 area summer price estimation results for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-1.7377	-18.56	lag 1	-0.26098	-34.53
trend	4.37E-06	3.04	lag 2	-0.21245	-27.19
pre_ ny2load	0.002714	22.86	lag 3	0.00565	0.71
ny2load1	-0.00197	-16.62	lag 4	0.110827	14.02
ny2load24	0.002458	22.73	lag 5	0.113693	14.33
ny2load25	-0.00293	-27.21	lag 6	-0.19672	-24.68
pny21	0.8964	912.94	lag 7	0.081792	10.16
pny224	0.516	398.1	lag 8	-0.03482	-4.31
pny225	-0.456	-328.97	lag 9	-0.02024	-2.51

c_24hour	-0.9841	-29.68	lag 10	0.081493	10.2
s_24hour	-0.203	-6.05	lag 11	0.079835	9.97
c_week	0.1382	7.43	lag 12	-0.03057	-3.85
s_week	-0.00596	-0.32	lag 13	-0.14905	-18.75
weekend cycle	0.4368	9.92	lag 14	0.044782	5.59
wp31	0.000021	0.06	lag 15	0.144387	18.07
wp32	0.001877	7.34	lag 16	0.056599	7.02
			lag 17	-0.02988	-3.7
			lag 18	0.131775	16.37
			lag 19	-0.0457	-5.73
			lag 20	-0.06911	-8.71
			lag 21	-0.00243	-0.31
			lag 22	-0.13863	-17.53
			lag 23	0.005763	0.74
			lag24	-0.02719	-3.6
		Adj R-Sq 0.9993			

Table A.39: NY2 area winter load estimation results for step 2

Variable	NYC winter load		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	132.756	35.67	lag 1	-0.61845	-81.38
trend	-0.00015	-7.05	lag 2	0.356167	39.86
ny2load1	0.9485	1108.01	lag 3	-0.02614	-2.8
ny2load24	0.7679	448.08	lag 4	0.048274	5.19
ny2loadc25	-0.7425	-410.29	lag 5	0.072024	7.73
c_24hour	-67.0308	-113.04	lag 6	0.102283	10.96
s_24hour	-8.894	-12.5	lag 7	0.108994	11.65
c_12hour	-60.7219	-61.92	lag 8	0.055458	5.93
s_12hour	-29.5677	-32.29	lag 9	-0.00866	-0.93
c_6hour	7.0752	11	lag 10	-0.03443	-3.7
s_6hour	10.404	16.14	lag 11	-0.04004	-4.3
c_week	5.0025	10.32	lag 12	-0.03359	-3.6
s_week	4.2184	8.74	lag 13	-0.01822	-1.95
weekend cycle	16.6045	12.96	lag 14	-0.02579	-2.77
hddc_24hour	0.4215	11.1	lag 15	-0.00545	-0.59
hdds_24hour	-0.7951	-19.63	lag 16	0.119283	12.8
hddc_week	0.3296	7.63	lag 17	-0.12084	-12.92
hdds_week	-0.0574	-1.26	lag 18	-0.02459	-2.63
hddweekendcycle	0.6162	5.71	lag 19	-0.03659	-3.92
hdd	0.8	7.05	lag 20	-0.00413	-0.44
sq_hdd	-0.00215	-0.73	lag 21	0.096372	10.35
			lag 22	0.006103	0.65

		lag 23	0.007462	0.84
		lag24	0.01578	2.08
	Adj R-Sq 0.9991			

Table A.40: NY2 area winter price estimation for step 2

Variable	NYC winter electricity price		Variable	Residual	
	Parameter Estimates	t Value		Parameter Estimates	t Value
Intercept	-1.2629	-5.5	lag 1	-0.25258	-33.38
trend	-1.1E-05	-5.11	lag 2	-0.21718	-28.16
pre_ ny2load	0.001867	11.27	lag 3	-0.06915	-8.83
ny2load1	-0.00071	-4.3	lag 4	0.109149	13.96
ny2load24	0.007094	54.03	lag 5	-0.02932	-3.73
ny2load25	-0.00794	-60.87	lag 6	-0.13009	-16.55
pny21	0.8605	747.6	lag 7	0.099694	12.59
pny224	0.5563	454.88	lag 8	0.118959	14.98
pny225	-0.4623	-330.25	lag 9	-0.00724	-0.91
c_24hour	0.5363	22.25	lag 10	-0.00218	-0.27
s_24hour	-0.4424	-13.22	lag 11	0.00844	1.06
c_12hour	0.1114	5.05	lag 12	-0.03515	-4.43
s_12hour	0.1844	8.73	lag 13	0.015912	2
c_6hour	0.8903	90.64	lag 14	-0.11768	-14.82
s_6hour	-0.0928	-9.27	lag 15	0.00025	0.03
c_week	0.2226	10.2	lag 16	-0.03774	-4.72
s_week	0.009325	0.43	lag 17	0.063191	7.96
weekend cycle	0.6425	13.62	lag 18	-0.01639	-2.07
wp31	0.001477	4.9	lag 19	0.041946	5.34
wp32	0.00047	2.19	lag 20	-0.00489	-0.62
			lag 21	0.091179	11.66
			lag 22	-0.12148	-15.51
			lag 23	-0.15833	-20.53
			lag24	0.094101	12.44
	Adj R-Sq 0.9991				

APPENDIX B

Figure B.1 to B.36: optimization results by different battery capacity among 6 regions in section 3.3

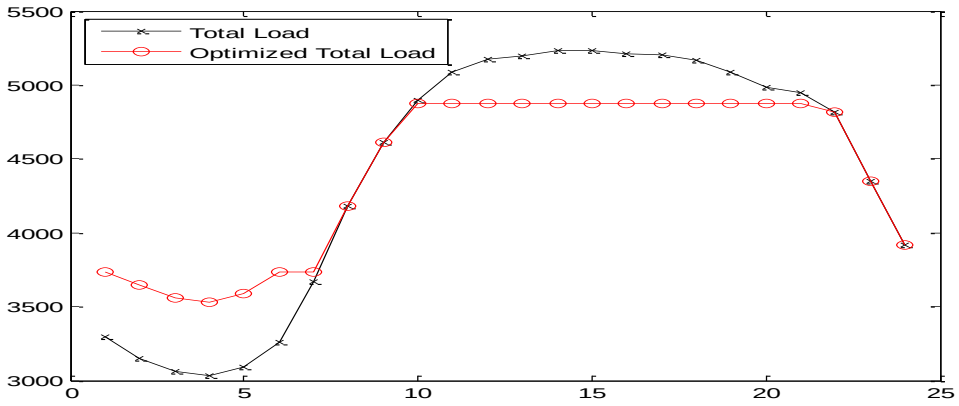

Figure B.1: optimized Total load in NE1 under 10% of STSL sum battery capacity

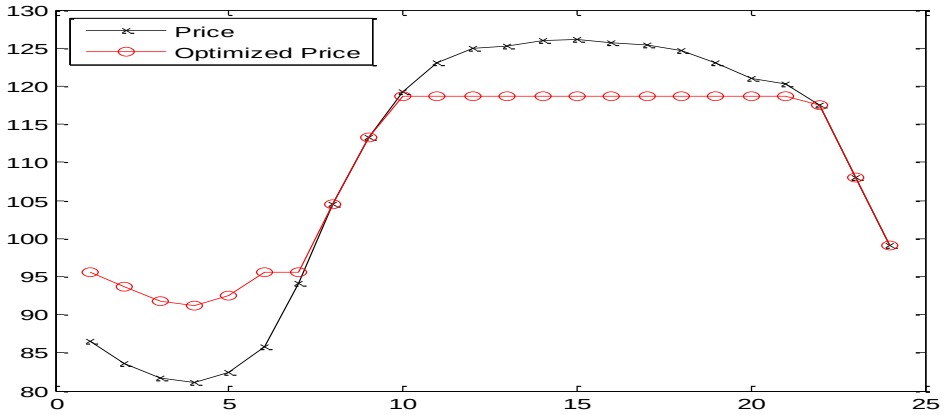

Figure B.2: optimized price in NE1 under 10% of STSL sum battery capacity

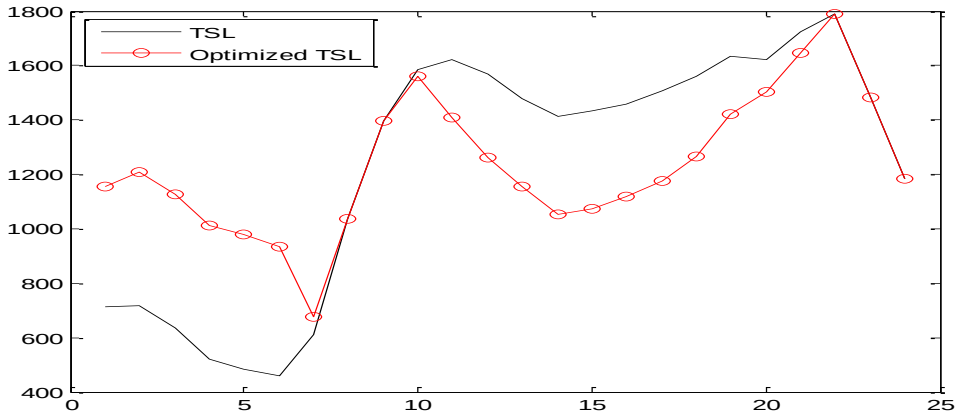

Figure B.3: optimized STSL in NE1 under 10% of STSL sum battery capacity

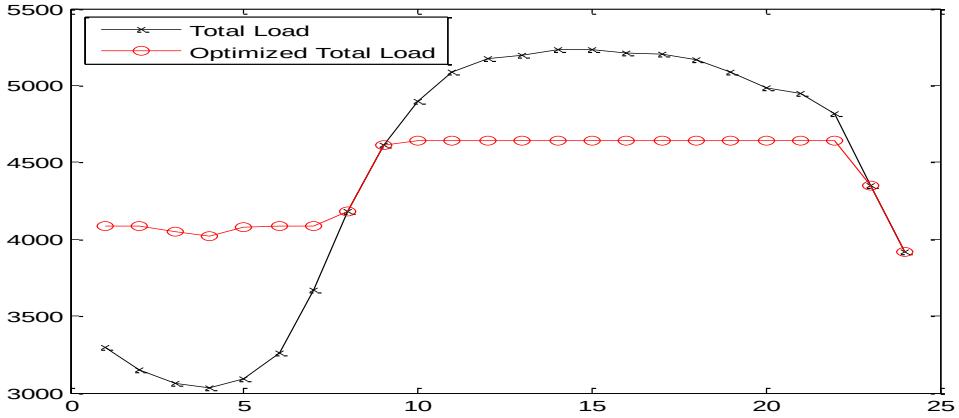

Figure B.4: optimized Total load in NE1 under 20% of STSL sum battery capacity

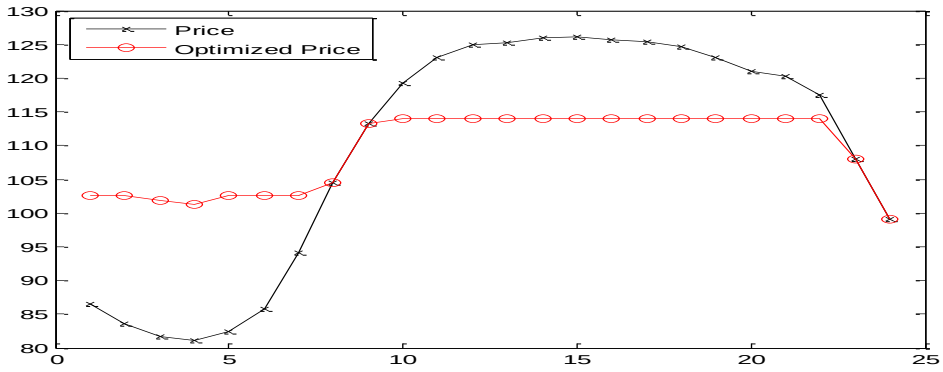

Figure B.5: optimized price in NE1 under 20% of STSL sum battery capacity

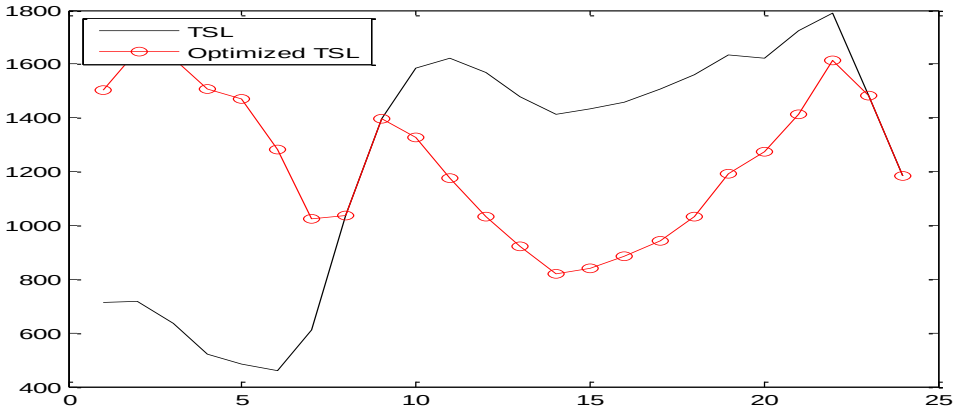

Figure B.6: optimized STSL in NE1 under 20% of STSL sum battery capacity

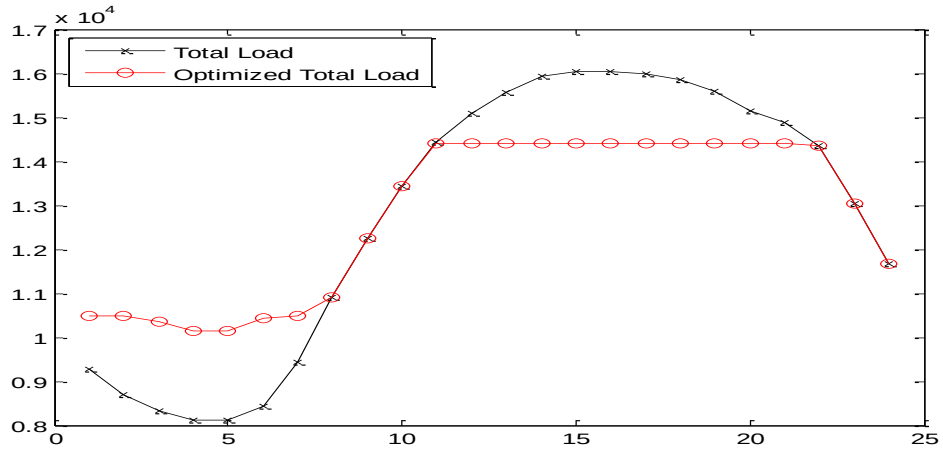

Figure B.7: optimized Total load in NE2 under 10% of STSL sum battery capacity

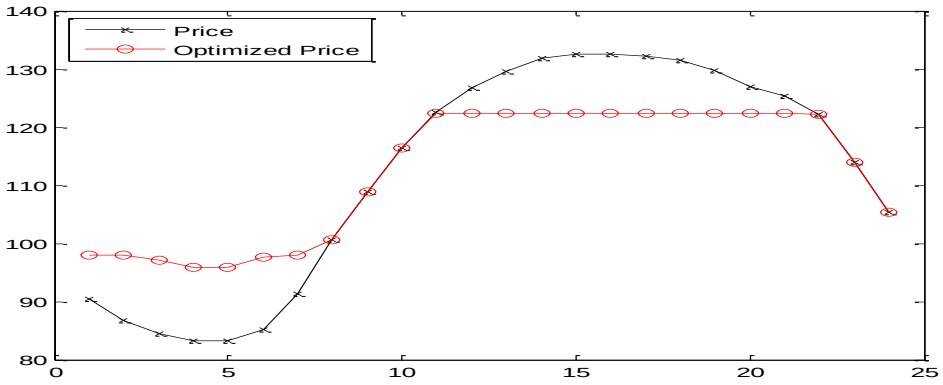

Figure B.8: optimized price in NE2 under 10% of STSL sum battery capacity

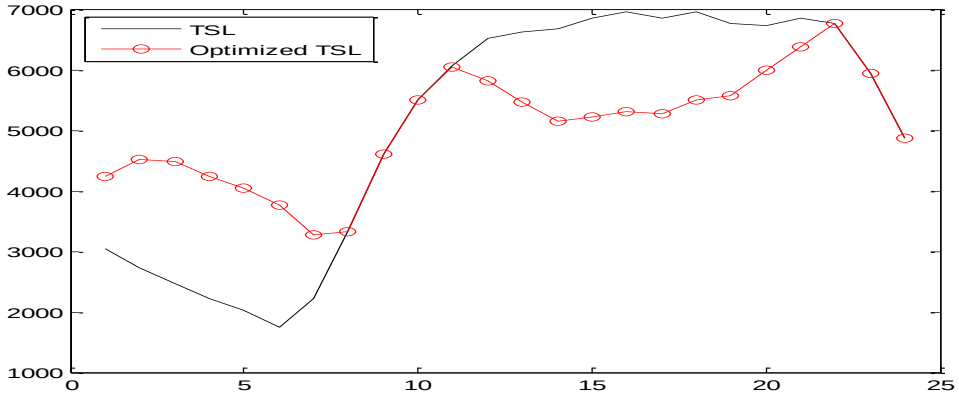

Figure B.9: optimized STSL in NE2 under 10% of STSL sum battery capacity

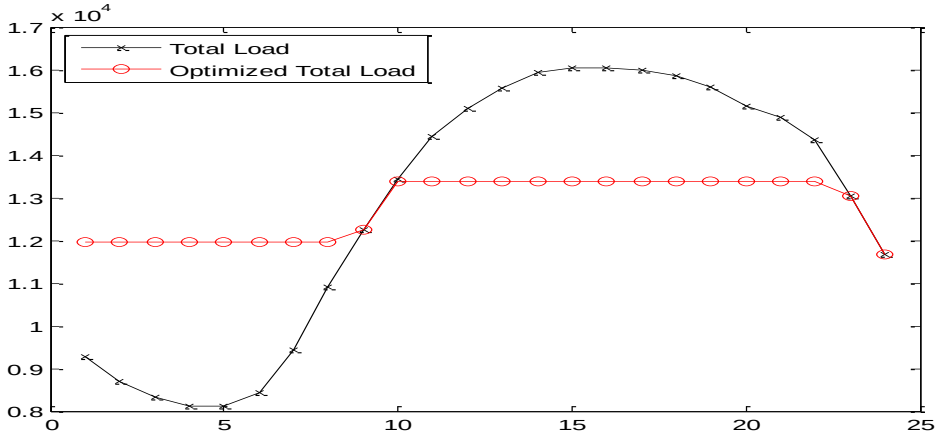

Figure B.10: optimized Total load in NE2 under 20% of STSL sum battery capacity

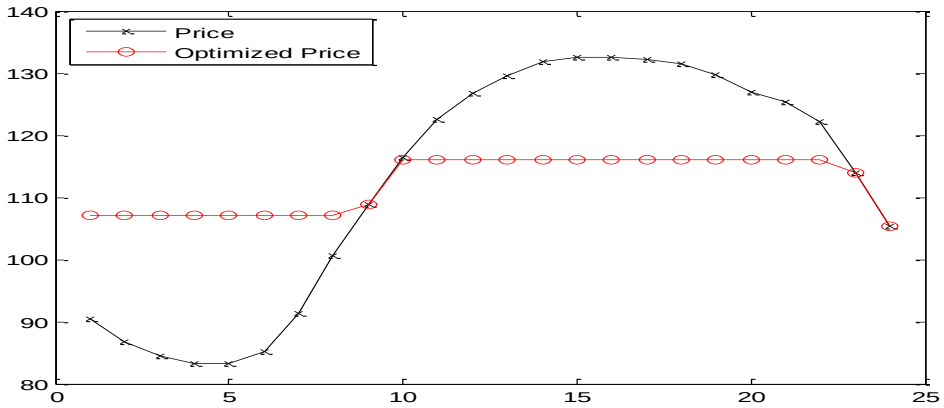

Figure B.11: optimized price in NE2 under 20% of STSL sum battery capacity

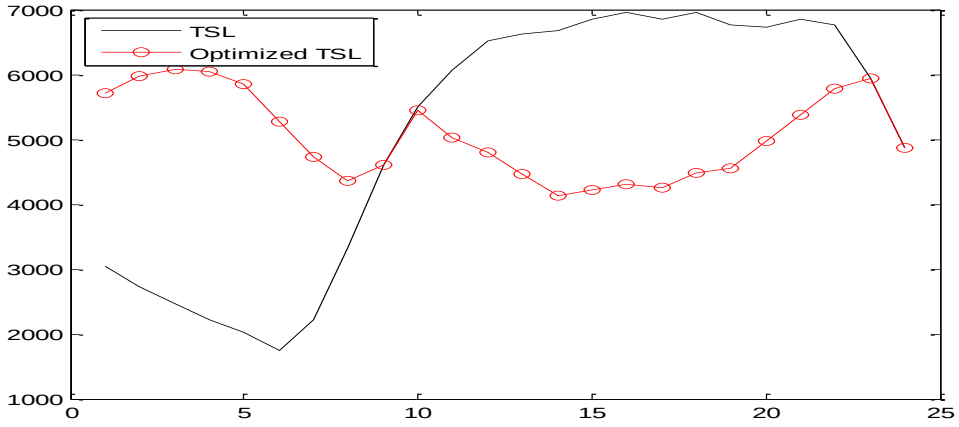

Figure B.12: optimized STSL in NE2 under 20% of STSL sum battery capacity

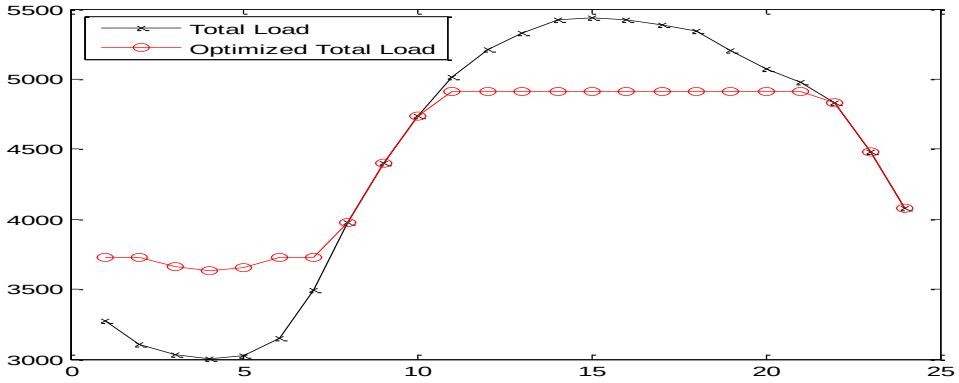

Figure B.13: optimized Total load in Boston under 10% of STSL sum battery capacity

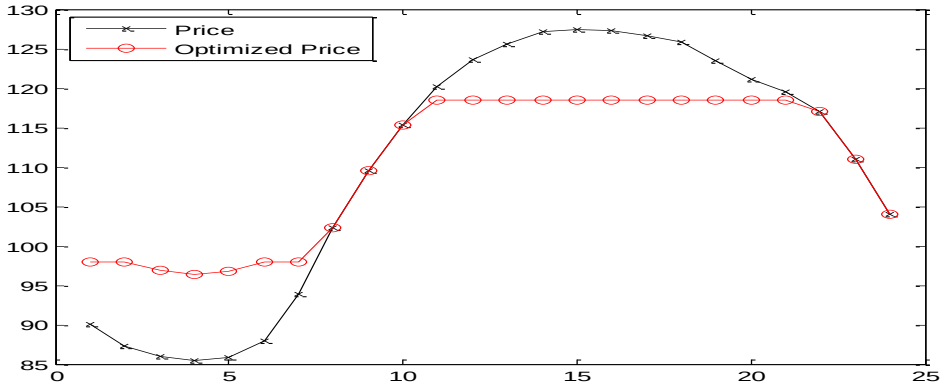

Figure B.14: optimized price in Boston under 10% of STSL sum battery capacity

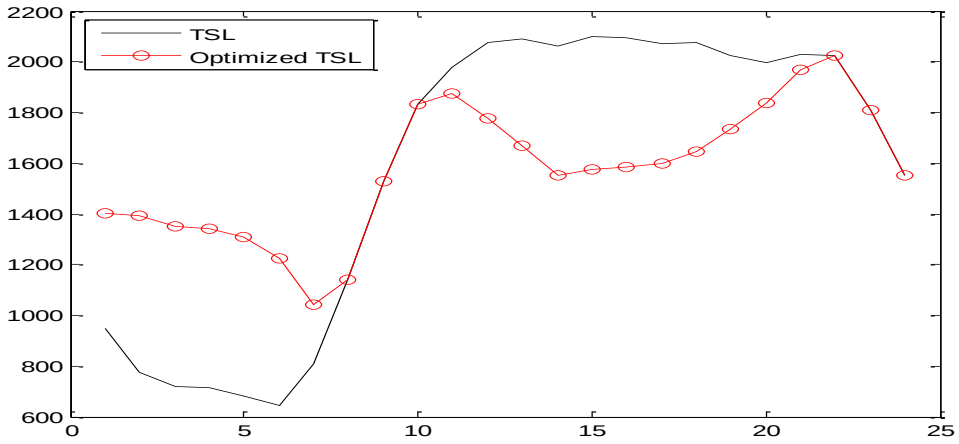

Figure B.15: optimized STSL in Boston under 10% of STSL sum battery capacity

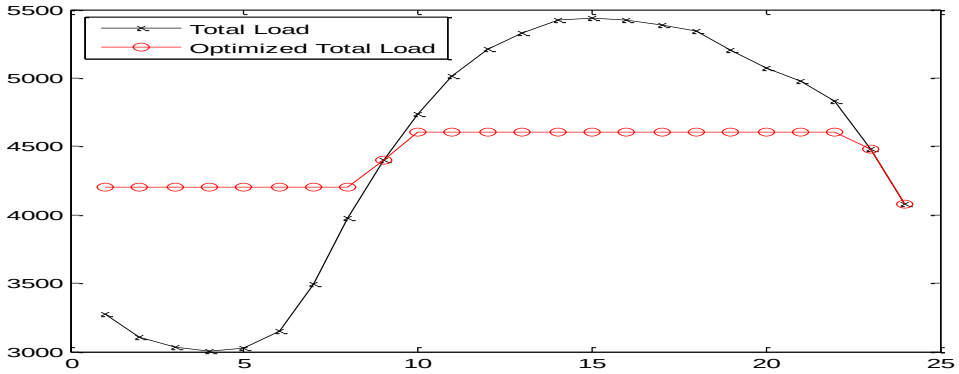

Figure B.16: optimized Total load in Boston under 20% of STSL sum battery capacity

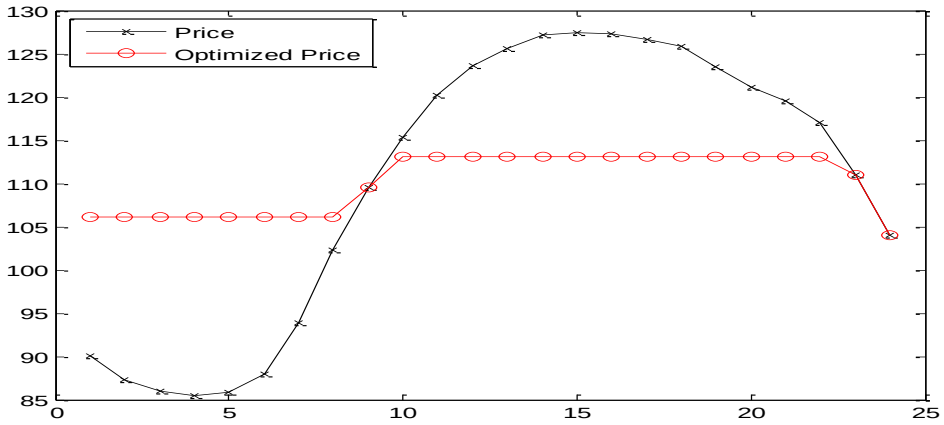

Figure B.17: optimized price in Boston under 20% of STSL sum battery capacity

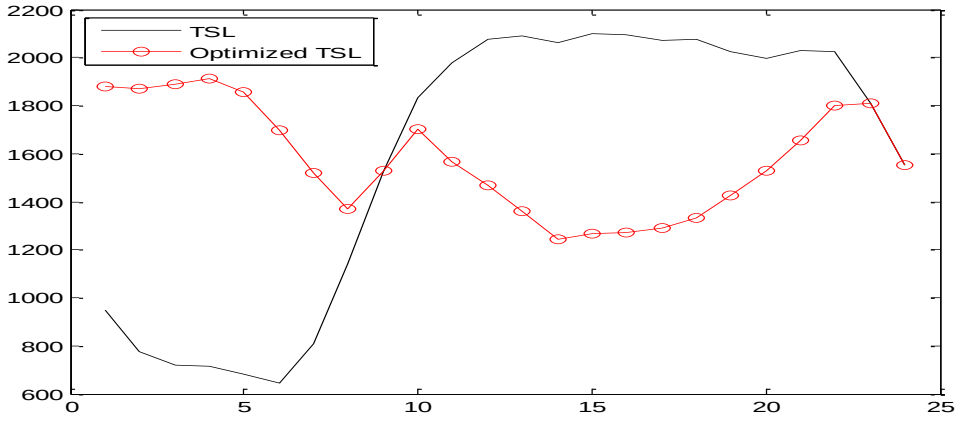

Figure B.18: optimized STSL in Boston under 20% of STSL sum battery capacity

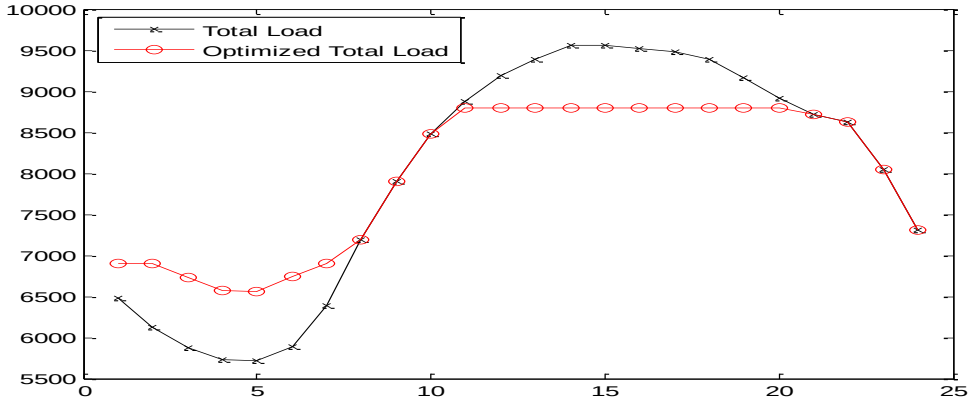

Figure B.19: optimized Total load in NY1 under 10% of STSL sum battery capacity

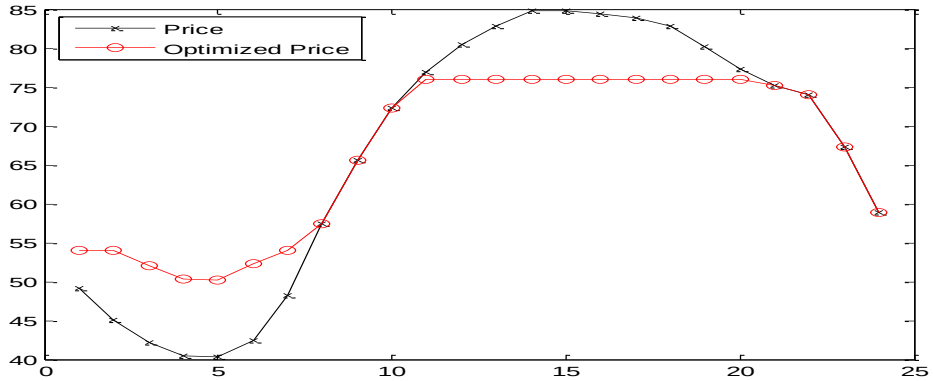

Figure B.20: optimized price in NY1 under 10% of STSL sum battery capacity

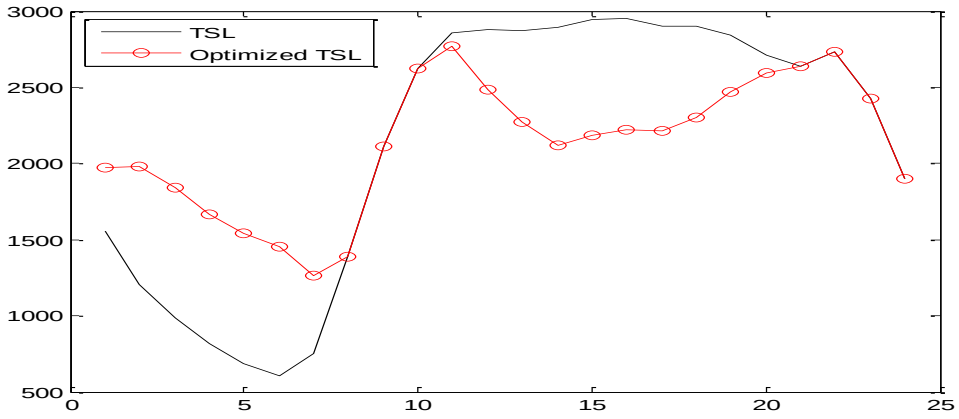

Figure B.21: optimized STSL in NY1 under 10% of STSL sum battery capacity

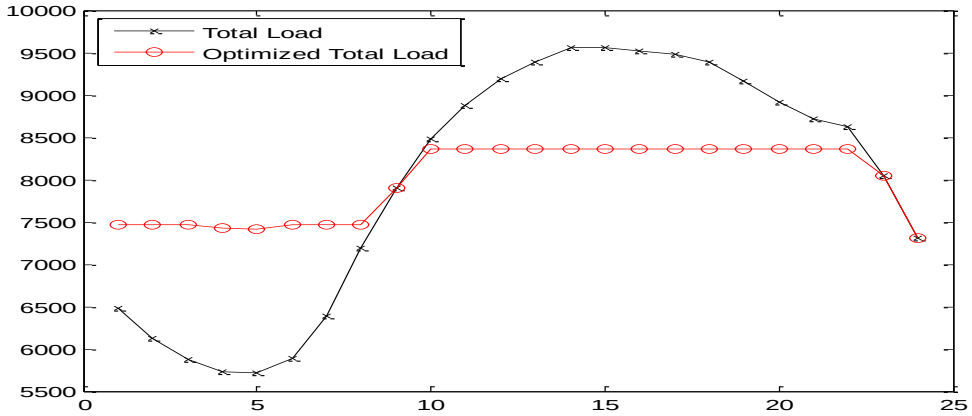

Figure B.22: optimized Total load in NY1 under 20% of STSL sum battery capacity

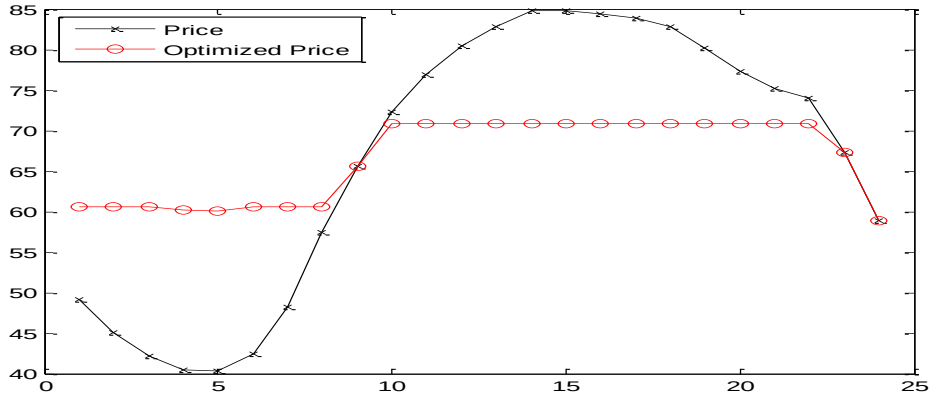

Figure B.23: optimized price in NY1 under 20% of STSL sum battery capacity

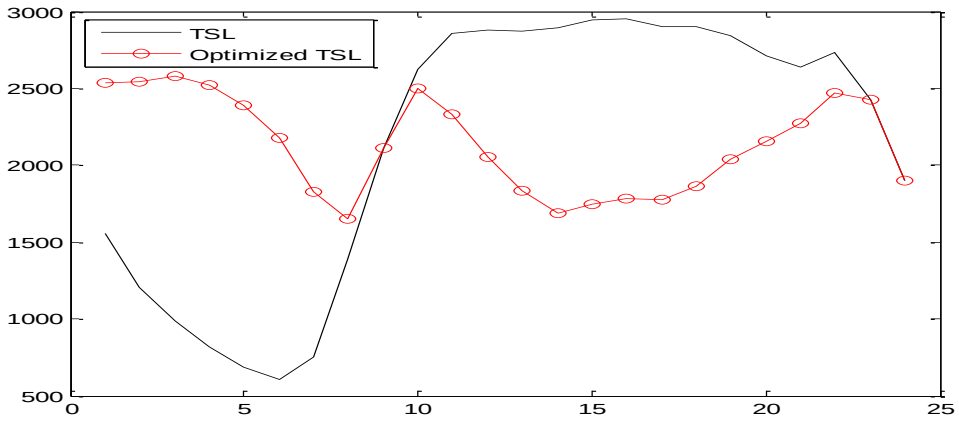

Figure B.24: optimized STSL in NY1 under 20% of STSL sum battery capacity

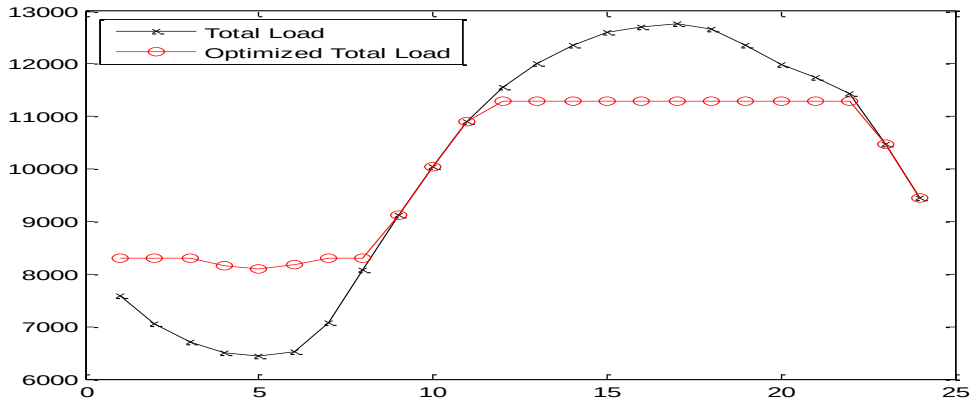

Figure B.25: optimized Total load in NY2 under 10% of STSL sum battery capacity

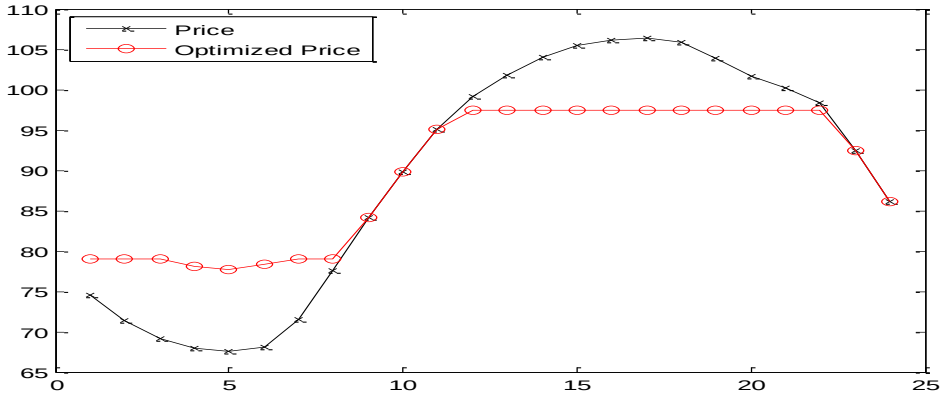

Figure B.26: optimized price in NY2 under 10% of STSL sum battery capacity

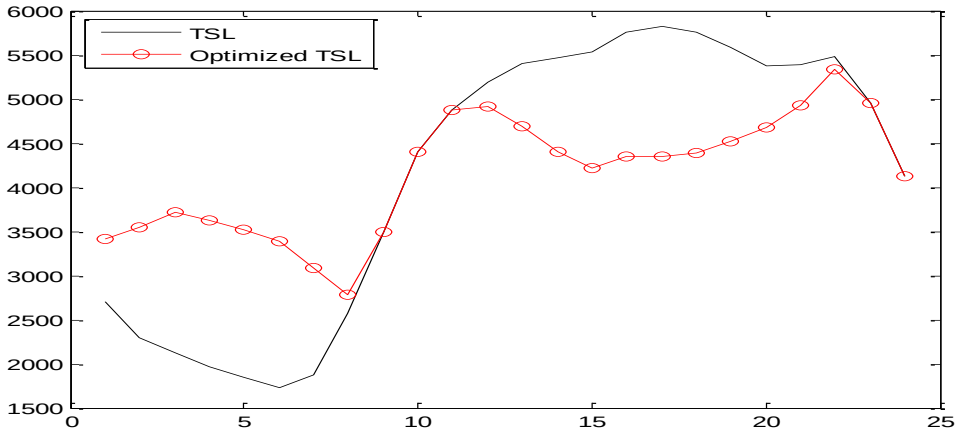

Figure B.27: optimized STSL in NY21 under 10% of STSL sum battery capacity

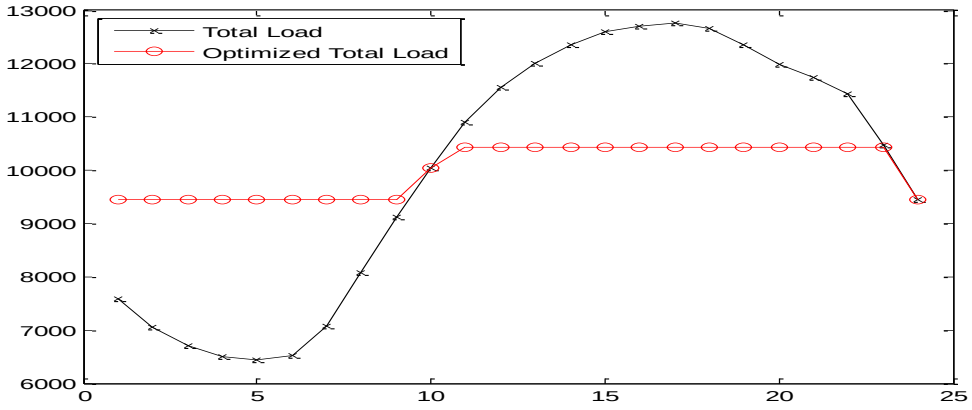

Figure B.28: optimized Total load in NY2 under 20% of STSL sum battery capacity

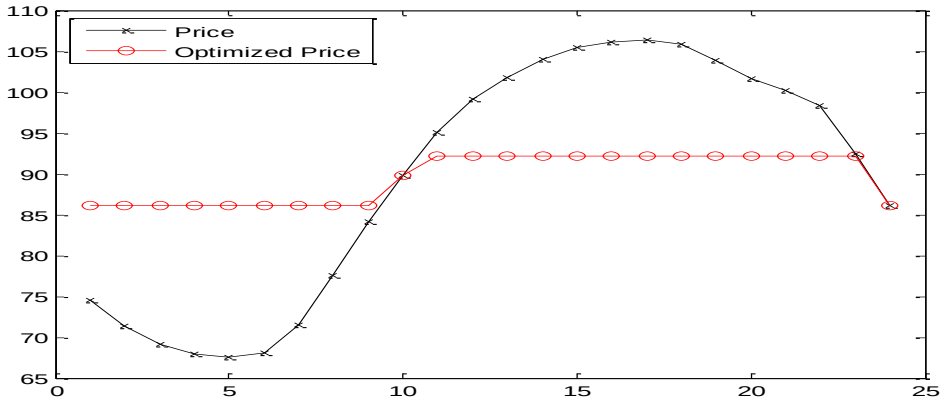

Figure B.29: optimized price in NY2 under 20% of STSL sum battery capacity

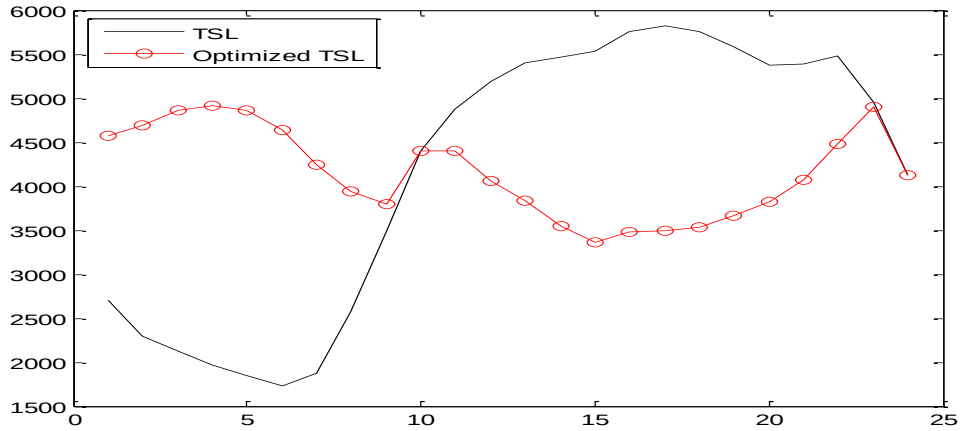

Figure B.30: optimized STSL in NY2 under 20% of STSL sum battery capacity

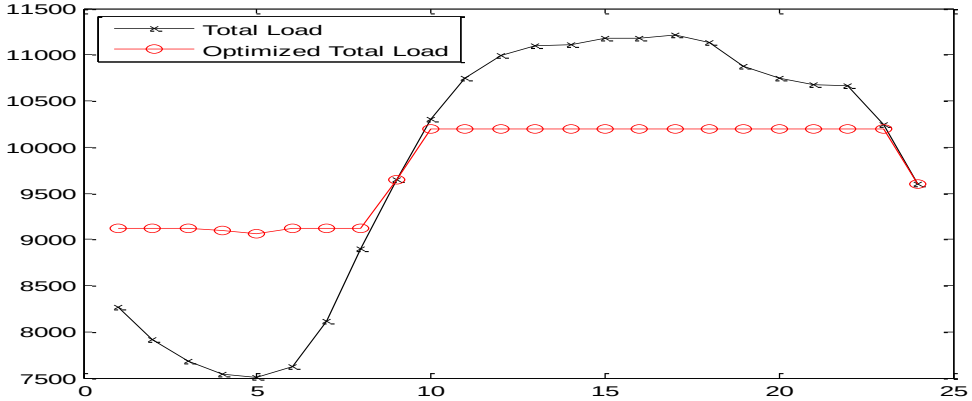

Figure B.31: optimized Total load in NYC under 10% of STSL sum battery capacity

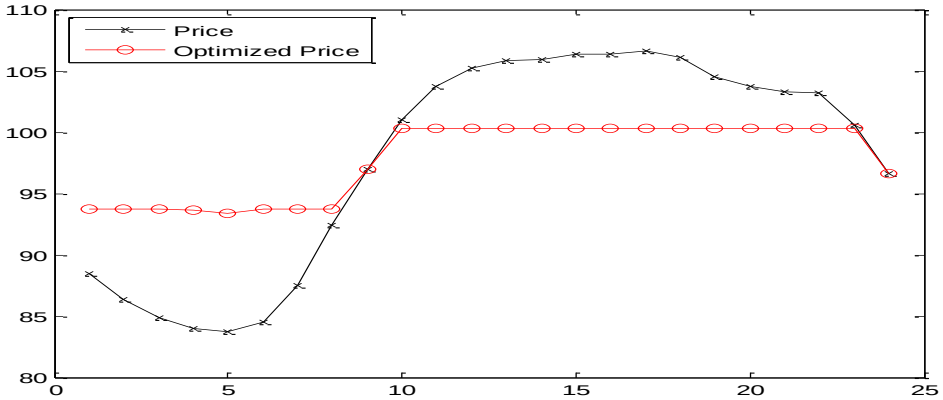

Figure B.32: optimized price in NYC under 10% of STSL sum battery capacity

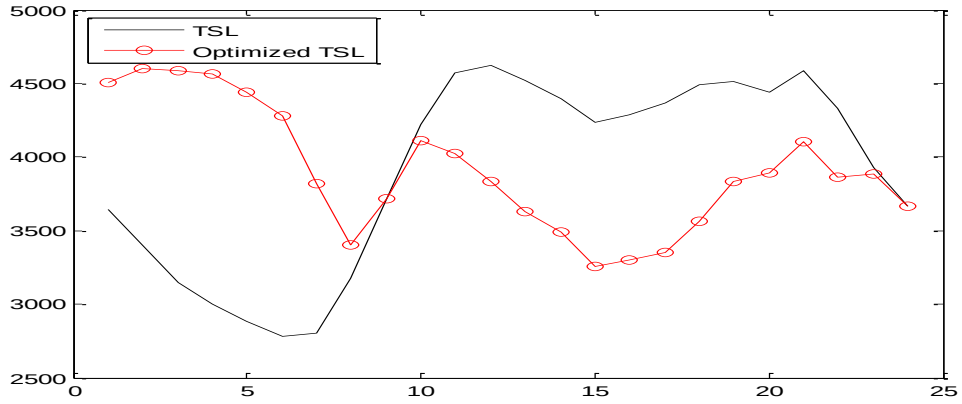

Figure B.33: optimized STSL in NYC under 10% of STSL sum battery capacity

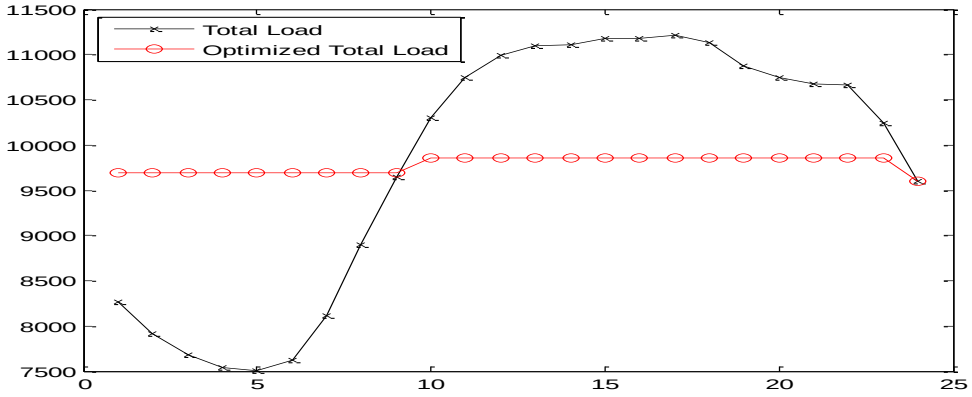

Figure B.34: optimized Total load in NYC under 20% of STSL sum battery capacity

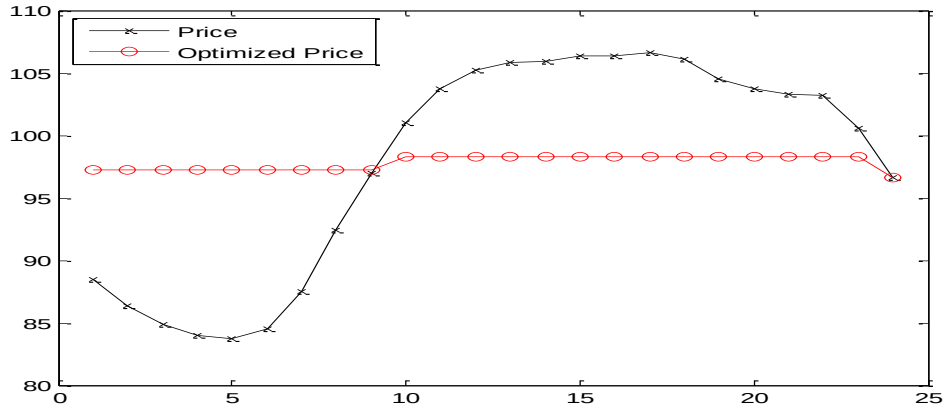

Figure B.35: optimized price in NYC under 20% of STSL sum battery capacity

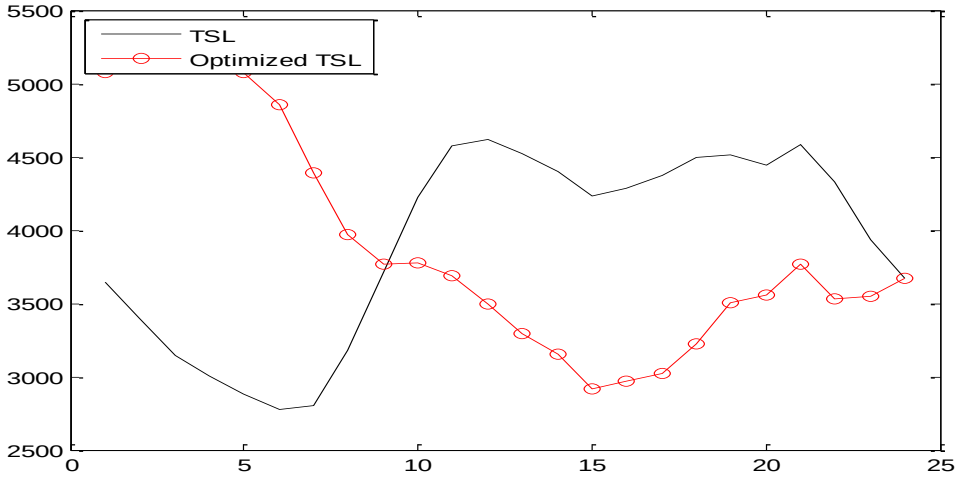

Figure B.36: optimized STSL in NYC under 20% of STSL sum battery capacity