EMISSIONS IMPACTS OF DYNAMIC PRICING

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science

by

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JANUARY 2015

ABSTRACT

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Dynamic pricing is a trendy term that can be found in a variety of industries. In the utilities industry, the implementation of dynamic pricing structure is an economic stimulus to encourage demand reduction of electricity usage in peak hours, when the power system is strained and the cost of electric power is very high. This study investigated the rate structure of day-ahead hourly pricing programs in New York State, and evaluated the demand and emissions impacts of dynamic pricing programs in the summer of 2008. Different scenarios of dynamic pricing programs are modeled to evaluate the demand and emissions change for NO_x and SO_2 emissions in peak hours, as well as in off-peak hours. Three methods are proposed to evaluate NO_x emission reduction in New York State. Hourly emissions changes from power production in the NPCC power system model are scaled to emissions in the National Emissions Inventory (NEI), in order to simulate potential emissions changes in historical days caused by dynamic pricing. The NEI and the simulated emissions are used as point source emissions input into Sparse Matrix Operator Kernel Emissions (SMOKE) modeling system. The processed emissions change from SMOKE is visualized using Visualization Environment for Rich Data Interpretation (VERDI). Results show that dynamic pricing programs can result in considerable emissions reduction in peak hours, while inducing a slight increase in off-peak hours. The

emissions reduction will have non-negligible environmental and social impacts for the New York State, especially for the metropolitan areas like New York City.

BIOGRAPHICAL SKETCH

Olivia was born November 17, 1988 in Jinan, China, where she grew up and stayed before coming to the United States. She went to Shandong University for a B. Sc. degree in Energy and Environment System Engineering. Influenced and inspired by Lin Cheng, former Dean of the School of Energy and Power Engineering, she developed a deep interest in energy and environment issue. Therefore, she came to Cornell University to continue her study, aiming to solve the imperative energy and environment problems that human beings are faced with, and will be faced with in the future. She joined the Energy and Environment Research Laboratory led by Prof. Zhang in August, 2011, where she continued her interests in energy and environment. At Cornell University, her main interest is on electricity market, power systems and emissions from power generation. Her thesis is focused on evaluating the emissions impact of dynamic pricing, which is a combination of economics, engineering and environment issue. The result of this research is important for policy making and regional resources planning for the government and power system operators.

ACKNOWLEDGMENTS

I treasure the time spent at Cornell University. Exposed in a totally different culture, I feel lucky that I have met all of you that helped me walk through this journey. First of all, I want to thank my advisor Prof. Zhang. Thanks to him, I have the opportunity to learn a lot at Cornell and research on energy and environment issue, which I have always been interested in. During the years in graduate school, he has helped me to grow with his knowledge and experience. He also introduced me to a lot of people and resources, which I deeply appreciate. I also thank my committee member, Prof. Mount for their availability to seek advice on economic issues. In addition, I want to thank Prof. Schuler, for his insight concerning the NYISO electricity market, and the inspiring he gave me on my career.

Next I want to thank my parents. They have been supportive on each decision I have made. They are the ones who are most concerned about if I am happy and healthy. Being 12 hours away, I feel sorry I couldn’t take care of them when needed.

Also, I would like to thank my friends as their support and accompany have kept me warm through the cold winters in Ithaca. Thank Xiaochen for the home-style cooking that really makes me feel at home. Thank my friends in the ECE MENG program, namely, Jinda, Hanbing, Yicong, Shuyan, Zhitu and many more who have helped me and worked with me along a couple of classes taken in the ECE department. Thank Yiping, who has been my friend since 7 years ago, and have been supportive all these years long. Thank the friends in the Society of Asian America Graduate Association (SAAGA). As Asians being a minority, I have learned from them how I should stand for myself in the society. Thank my friends in Sibley Graduates in Mechanical and Aerospace Engineering (SiGMA), especially Vlad. It was

great working with them and arranging events for the fellow students in the department. I also want to thank Marcia and Emily for their help in providing funding and arrange locations.

Last but not the least, I want to thank my special one, Keenan. Thank you for all the time you spent with me, day and night. I am glad and grateful that I have found my new family in this country.

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CHAPTER 1

INTRODUCTION

Over the past decades, electricity consumption has been growing with the economic growth, and it is still expected to grow in the future. Moreover, peak demand is growing faster than electricity demand [1]. Concerns have been raised about high electric demand on peak days, especially in a hot summer.

Peak demand affects human life in several ways. Firstly, costs in procuring energy, acquiring and maintaining adequate capacity during peak hours is much higher than that during off-peak hours. However, faced with a flat retail electric price, the majority of customers are not aware of the fluctuating price in the wholesale electricity market. Therefore, the demand for electricity is not always well matched with the generation supply in the electricity market throughout the day. Electricity is being over-consumed during the peak hours and under-consumed during off-peak hours. This results in deadweight loss and thus low economic efficiency. Therefore, some state that a price responsive demand greatly increases economic efficiency [2][3]. Next, the transmission system is bearing much stress in peak hours, which can lead to severe power outages, imposing large financial loss for businesses and lots of inconvenience for everyday life. For example, in 2012 the blackout that stroke India affected 620 million people, 10% of the world’s population. Last but not the least, intense power generation on peak days, often provided by more costly and dirtier plants, has significant impacts on the environment and human health. It is shown that NO_x emissions from electric generating units double on peak days in New Jersey, downstate New York and New England region [4]. NO_x is a main source of ozone precursors. High concentration of ground level Ozone is known to have adverse health effects on human beings, especially irritation of the respiratory system. However, some states in the northeast of United States have been among the 8-hour ozone nonattainment areas according to the 1997 and 2008 National Ambient Air Quality Standard(NAAQS) [5][6][7]. Meanwhile, acid rain, mainly caused by SO_2 and NO_x emissions from burning fuels, negatively affects water and soil which are essential parts of human life as well. It is without doubt that on high electric demand days, the air pollutants from fossil fuel combustion will largely aggravate the environmental problems. Therefore, reducing peak electricity demand is the key to alleviate the economic and environmental problems stated above.

With growing peak demand causing those problems, several methods have been brought up to address the challenges. Demand-side management has been a main focus over the past two decades, among which energy efficiency and load management are the most popular programs. Energy efficiency, while more often considered to reduce customer energy use on a permanent basis, has proved to be able to achieve great peak demand reduction [8]. On the contrast, demand response was designed for load curtailing and shifting on high electricity demand days, thus has great potential in peak load reduction [9]. What's more, integration of plug-in hybrid vehicles in the grid for peak reduction on high electric demand days can also yield considerable benefits economically and environmentally [10]. In addition, installing emission control equipment at the power plants is a direct way to control emissions from the sources.

A study conducted by the brattle group illustrated that dynamic pricing programs in New York State can reduce total resource costs, lower customer market costs, and improve economic efficiency [11]. However, there is little discussion about how dynamic pricing can affect the environment, which is also an important part of human life. This thesis studies the potential environmental impacts of dynamic pricing in the Northeast Power Coordinating Council (NPCC) region through modeling dynamic pricing programs in New York State. It shows that by implementing dynamic pricing rate structure in the retail electricity market, the demand reduction during peak hours from various customers can lead to considerable emissions reduction across the NPCC region, thus bringing huge environmental benefits.

CHAPTER 2

DYNAMIC PRICING AND EMISSIONS

2.1 Introduction

High electricity demand on peak days leads to tremendous air pollution, and puts the power system under stress. The electric generating units (EGUs) that are operated during peak times are often old, dirty, and less efficient ones. The emissions from the EGUs, especially NO_x, are precursors of Ozone. Ground-level ozone can induce public health problems, such as harming lung function and irritating respiratory system. Ozone has been a problem for the northeast region of the United States, with exceedances of the 8-hour ozone National Ambient Air Quality Standards (NAAQS) on hot summer days [1].

Strategies and technologies of demand-side management have been raised to address peak demand problems and maintain system reliability. Also, whether or not they will be conductive to alleviating the environmental problem is getting growing attention. For example, a recent study suggests that without proper emission control, the participation of behind-the-meter generation in demand response programs may result in significant NO_x emissions, contributing to the formation of ozone pollution [2]. Also, regulated charging of plug-in hybrid electric vehicles in summer proves to produce significant overall emissions reductions for NO_x [3][4][5].

Dynamic pricing (DP) is a time-varying retail rate structure that passes through the wholesale electricity market spot price. Better reflecting the cost of energy, it provides a price signal to the customers, giving incentives to curtail and/or shift usage during the peak hours. By reducing peak demand, dynamic pricing can potentially reduce the need to install additional generation and transmission infrastructure to meet capacity requirements. There are several types of dynamic pricing program, e.g. time-of-use pricing, real-time pricing, and critical-peak pricing. Hopper et al finds that large customers that respond to day-ahead hourly price are influential in reducing peak load and maintain system reliability [16]. It is also revealed that hourly pricing programs can provide stable and sizable demand reductions for residential customers [17]. A report by Navigant Research shows that dynamic electricity pricing will be available to about 14% of utility customers by 2020, in spite of the existing mythology that stalls the move to dynamic pricing[18][19]. Given that hourly pricing programs has proved to produce significant peak load reduction, day-ahead real-time is modeled and evaluated in this study. Also, it better reflects the wholesale market conditions. The objective of this study is to evaluate the environmental impacts of dynamic pricing in New York State, particularly on NO_x emissions from EGUs.

2.2 Methodology

In March 2008, EPA strengthened its NAAQS for ground-level ozone, revising the 8-hour primary and secondary ozone standard to a level of 0.075 parts per million (ppm) from the previous 1997 standard of 0.08 ppm. The year 2008 from June to September was studied to see if DP programs will help meet the new standard in hot summer days.

It is assumed all retail customers in New York State are subject to dynamic rates, in order to maximize the potential benefits brought by dynamic pricing. Under dynamic pricing programs, flat and dynamic retail electricity prices were constructed, then the impacts of dynamic pricing on demand was calculated depending on customer elasticity. Emissions impacts were evaluated using different methods.

2.2.1 Retail Price Modeling in New York State

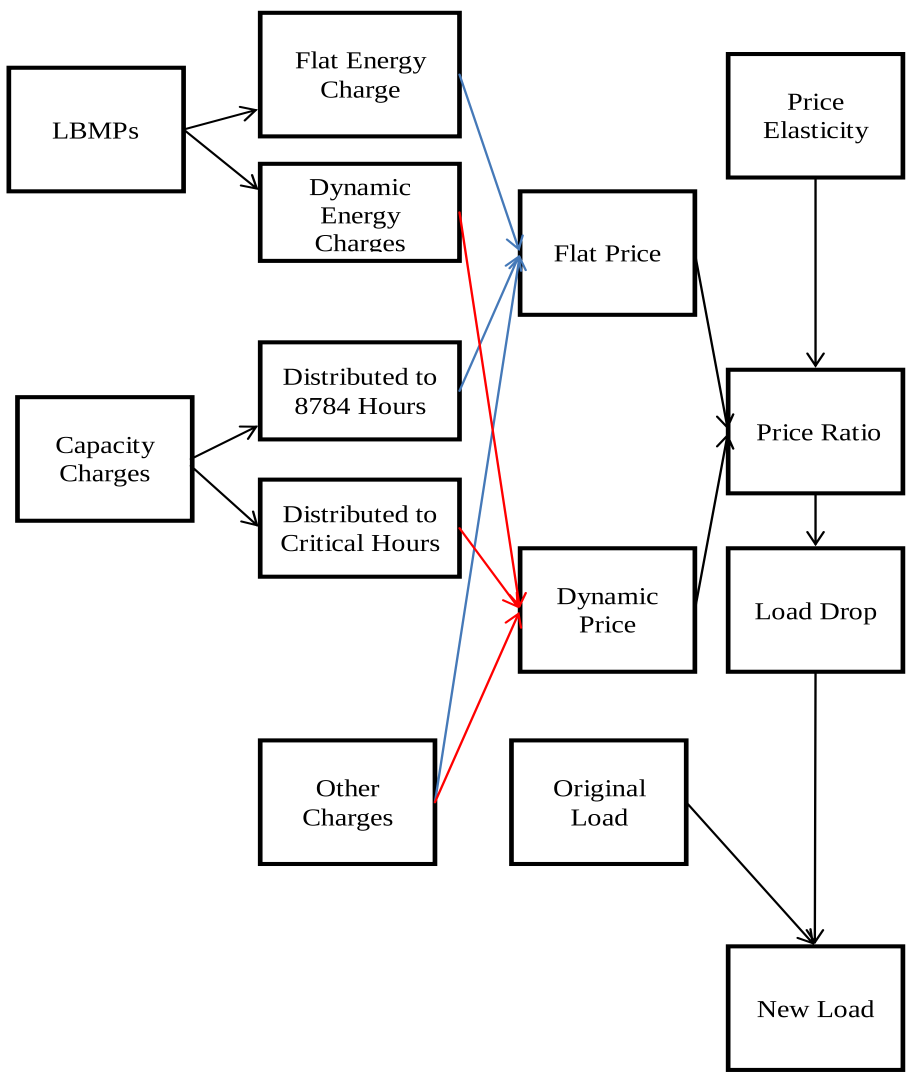

Figure 1. Dynamic Pricing Methodology Flow Chart

The methodology of dynamic price modeling is demonstrated in Figure 1, following the New York Independent System Operator (NYISO) report [11]. Electricity rice based on 3 components: energy charge, capacity charge and other non-generation charges. Hourly prices are modeled by zone, while 3 regions are mainly considered here: Zone J (New York City), Zone K (Long Island) and ROS (Rest of System). The methods on calculating prices are elaborated in the Appendix A. Flat rate and dynamic rate of energy and capacity charges are calculated separately for flat price case and dynamic price cases, while other charges are assumed to be the same for both cases. Then the charges are combined to get flat and dynamic electricity prices. Then the ratio of dynamic to flat charges is calculated, and demand elasticity is applied to the ratio to evaluate the DP effects on the demand.

Then demand changes in each hour are decided by the customer elasticity. Demand elasticity is observed through pilot experiments. There are several studies on pilot experiments rate designs and price elasticity evaluation [20-24]. The relationship between price ratio and the amount of peak reduction is found by surveying pricing pilot experiment and was quantified as a logarithmic model [25]. The logarithmic model of elasticity curve is extrapolated to model the load shifting in off-peak times, shown in Figure 2. The experiments with enabling technology, such as in-home displays and programmable thermostats produce larger demand reduction, thus it is described in a different curve. The logarithmic model shows that the amount of demand reduction rises at a decreasing rate with the increasing of price ratio.

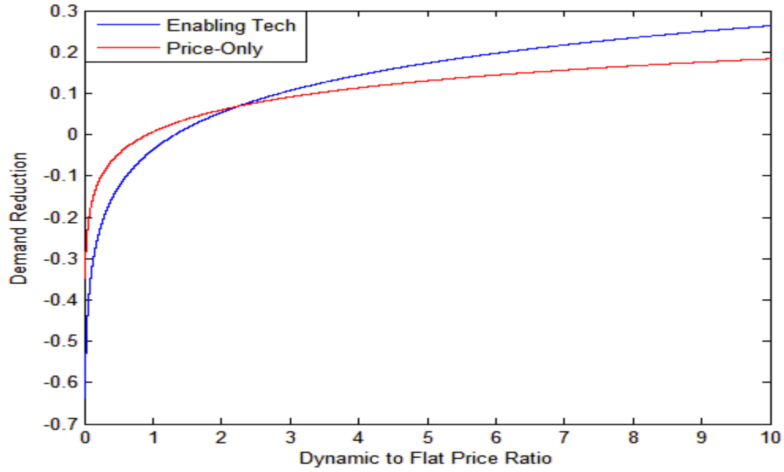

Figure 2. Demand Curves: $y = a + b\ ln(Price\ Ratio)$

During peak time, the ratio of dynamic price to flat price is larger than one, while during off-peak time, the ratio is smaller than one. In our base case, the load reduction during peak time is up to 16% with the price ratio around 8, and the load increase during off-peak time is up to 7% with the price ratio around 0.36. In the base case with enabling technology case, the maximum load drop is 23.7%.

2.2.2 Emissions Modeling in New York State

Different methods are proposed in this study to evaluate the environmental impact of dynamic pricing, and to bound the uncertainties in the analysis. One perspective is to evaluate the emissions from marginal generators by simulating the economic dispatch in the NPCC region. The other perspective is to identify peaking units by emissions requirements and by capacity factors.

2.2.2.1 Economic Dispatch Based Emissions Modeling

In this approach, we propose a network-constrained economic dispatch (NCED) method. Emissions changes due to dynamic pricing programs in New York State are derived through a power system model in the NPCC region. MATPOWER, a MATLAB-based power system simulation tool based on economic dispatch under network constraints is used to solve optimal power flow in the reduced NPCC network [26]. The inputs to this power system model include the original zonal hourly load from NYISO, Independent System Operator New England (ISO-NE), Pennsylvania, Jersey, Maryland Power Pool (PJM), Independent Electricity System Operator (IESO) websites, as well as the DP New York zonal hourly load. One of the outputs of this model is unit-level hourly power generation from each of the 693 generators in the NPCC network. NO_x and SO_2 emissions rates of each generator are also derived within the model. Comparing original case with the dynamic pricing cases, hourly power output rises or decreases due to marginal dispatch of fuel generators under network constraints. Accordingly, emissions rates from each generator on the grid also change due to power re-dispatch.

2.2.2.2 Scenario Based Emissions Modeling

2.2.2.2.1 Targeted Peaking Units

In the peaking units (PU) method, NO_x emission changes are evaluated by targeted peaking units in New York State. According to a NYISO report conducted by NERA Economic Consulting, generators within the annual operating hour threshold to avoid Lowest Achievable Emission Rate (LAER) and Best Available Control Technology (BACT) requirements for NO_x emission were identified as peaking units [27]. Peaking units run only when there is a high demand, while in our study, they are assumed to be running during critical hours. To quantify NO_x reduction during critical hours, emission factors of the peaking generators are calculated from EPA Air Markets Program Data, and total NO_x emissions are calculated using a weighted average method, according to their generation output [28].

$$Emission\ Factor_i = \frac{NOx\ Rate_{Avg,i} Heat\ Input_i}{Gross\ Load_i}, \forall i \in \{Peaking\ Units\} \quad (1)$$

$$\Delta Emissions = \sum_{\forall i \in \{Peaking\ Units\}} \left(Emission\ Factor_i\ \ \Delta Load \frac{Generation_i}{\sum_{\forall i \in \{Peaking\ Units\}} Generation_i} \right) \quad (2)$$

2.2.2.2.2 Targeted Capacity Factors

The capacity factor (CF) method is also based on EPA Air Markets Program Data. The generators in New York State are ranked by their capacity factors. Capacity factor is the ratio of the generator's actual output over a year to the maximum output it could produce at full nameplate capacity over a year. The generators with lower capacity factors are considered being operated during peak demand periods. There are some units with very short operating times over the year, which are only dispatched on the hottest days in the summer. One peak days in the summer, NY zonal load profiles under DP programs are derived, and compared with the original load profiles. For each hour with demand reduction, the supply is stacked using units with lowest capacity factors while keeping total generation and load balanced. Each dispatched unit runs at full production except the marginal unit. The emission factor per unit and total emissions are described in equation 5 and 6.

$$Emission\ Factor_i = \frac{NOx\ Rate_{Avg,i} Heat\ Input_i}{Gross\ Load_i}, \forall i \in \{Dispatched\ Units\} \quad (3)$$

$$NO_x\ Emission = \sum_{\forall i \in \{Dispatched\ Units\}} Emission\ Factor_i\ Generation_i \tag{4}$$

2.3 Results and Discussion

2.3.1 Demand Reduction Evaluation

2.3.1.1 NYISO Load Duration

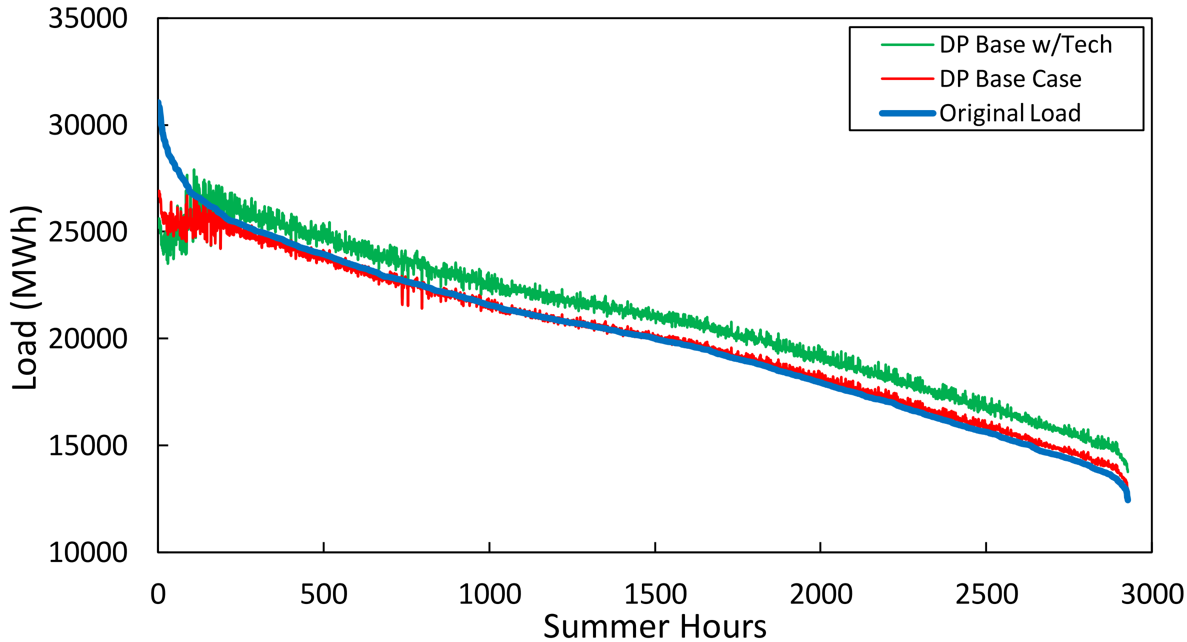

Figure 3. NYISO Load Duration Curve

Figure 3 is the NYISO load duration curve of the NPCC network from June to September of 2008. The blue line shows the original NYISO load. The red and green line depicts the new NYISO load under base case DP program and base case with technology. This load duration figure clearly shows that during critical hours, DP program effectively reduces the New York peak load by a significant amount. Meanwhile, for non-critical hours there is slight demand increase. Apparently, the load increase in non-critical hours is small compared to the load decrease in critical hours.

Also, base case with technology produces more load reduction during critical hours than base case, while induces more load increase during non-critical hours.

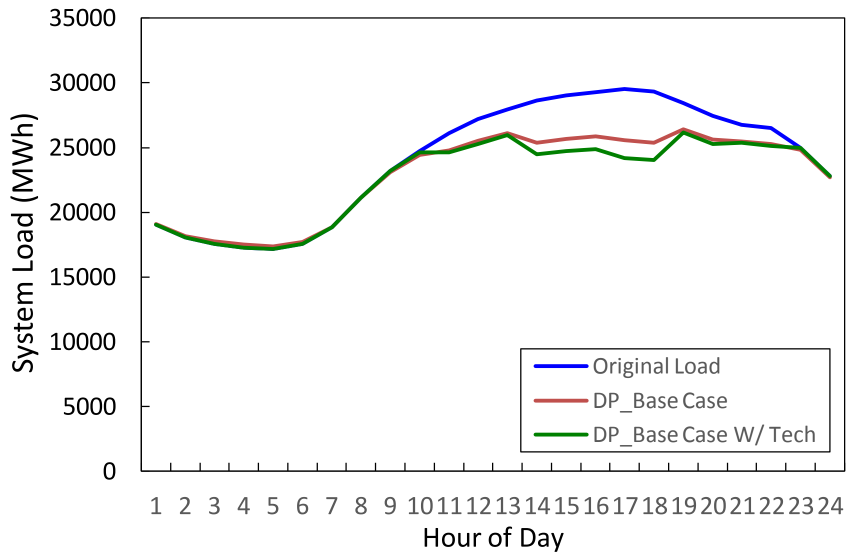

Figure 4. Original NYISO Load and DP Loads on July 8th, 2008

Figure 4 compares the base case dynamic pricing program and the base case with technology program. It shows dynamic pricing programs effectively reduce the peak load in New York State. The red line shows that base case scenario works well in flattening the peak load and smoothing the overall load curve, both of which are beneficial for the power systems. In the dynamic pricing programs with enabling technology, there is more demand reduction in the peak hours, which can reach up to 23.7% as compared to 16.79% in the base case. However, the shoulder hours might become the new peak hours that set the capacity requirement.

2.3.1.2 Demand Reduction for Different-Hours Dynamic Pricing Scenarios

In addition to applying technologies along with implementing dynamic pricing programs, demand changes with different pricing scenarios are also evaluated. Following the NYISO report, the scenarios vary by changing the number of critical hours in the dynamic pricing programs, shown in Table 1. For the More-Hours Case, we nearly doubled the number of critical hours; while in the Fewer-Hours case, the number of critical hours is cut by half.

Table 1. Dynamic Pricing Scenarios

Critical Hours	Upstate	New York City	Long Island
Base Case	80	90	50
More-Hours Case	150	180	90
Fewer-Hours Case	40	50	30

The total load reductions from different dynamic pricing scenarios are shown in Table 2. It is shown that fewer-hours case can induce larger percentage demand reduction in peak hours, whether it is for a single hour, or considering all the critical hours in the summer. However, it causes less total energy reduced during the whole summer compared to other scenarios. The asymptotically-zero slope of the logarithmic price-demand elasticity model shows that as critical peak hours decrease, prices increase, but demand does not reduce by a commensurate amount. In summary, more critical hours increase overall load reduction, while fewer critical hours further decrease the peak load.

Table 2. Comparison of Demand Reduction

	Base Case	Fewer-Hours	More-Hours
Total Demand Reduction (GWh)	185	118	274
Maximum Single Hour Demand Reduction Within Critical Hours (%)	16.8	21.2	12.9
Maximum Zonal Peak Load Reduction Within Critical Hours (%)	14.6	19.1	11.1
Load Reduction Over All Hours (%)	0.3	0.2	0.5

It is also valuable to assess the effects of dynamic pricing programs on a particular day in urban area. July 8th is a typical critical day in summer of 2008. Figure 5 shows how these 3 different dynamic pricing scenarios will change the demand in New York City. All 3 cases help reduce the peak load to different extents. However, by examining the load shape, deeper valley is noticed when decreasing the number of critical hours. More load reduction within fewer hours result in a sharper shoulder. The shoulder is not favorable due to the following reasons: On one hand, it will incur more ramping cost for the generators to shut down and turn back on again. On the other hand, the goal of dynamic pricing is to flatten the load. If peak load is reduced to be smaller than the off-peak load, then it will no longer be considered as critical. Thus the extra reduction is not necessary, even harmful for the system. This problem might also been seen in the base case with technology, as indicated in figure 5. However, fewer-hours case has an advantage in real life. It means there are fewer days and hours when very high electricity prices are observed. Customers might be more likely to respond to high prices if there are not that many of them. All in all, there are pros and cons under each dynamic pricing scenario, but there is considerable demand reduction under each the dynamic pricing scenario. For the customer cost evaluation, see Appendix B.

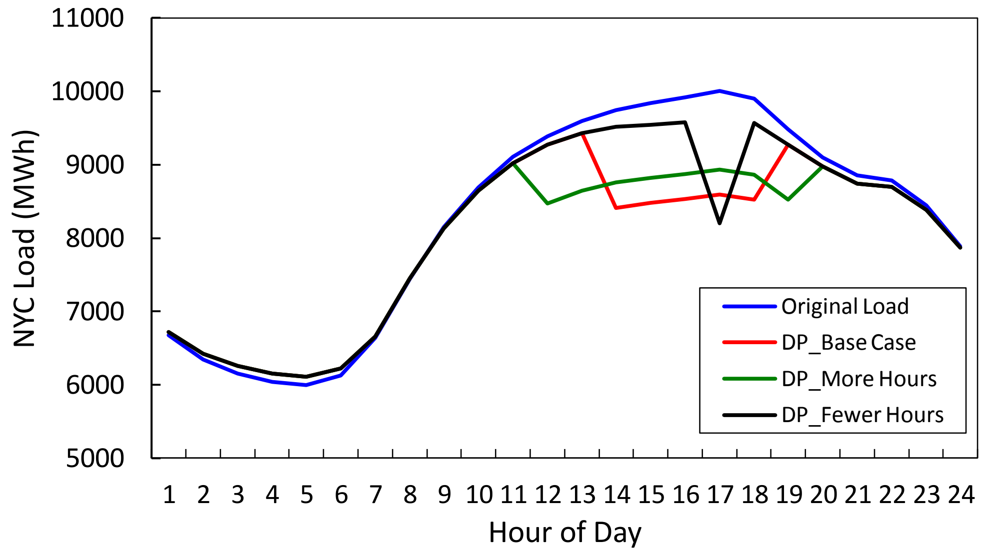

Figure 5. Original NYC Load and Load under DP Programs on July 8, 2008

2.3.2 Emissions Reduction Evaluation

2.3.2.1 Emissions Reduction based on Power System Model

Based on MATPOWER model, after implementing dynamic pricing rate structure, emissions from some generator change as a result of power production change. To further evaluating the environmental impact, emission changes are evaluated on a state basis. Results in Table 3 show that for the base case dynamic pricing scenario, there are 6.7 tons NO_x reduction on a typical hot summer day, July 8th, 2008 in New York State, which accounts for 4.05% of the total emissions. Compared with the NO_x reduction goal of New York State, which is 50.8 ton NO_x per day, dynamic pricing can achieve about 13% of the total reduction goal [29].

Compared with other cases, the more-hours case has slightly more NO_x reduction in New York than the base case, given the fact that it does not have the most load reduction for the day, nor does it have the most NO_x reduction for all the states in the NPCC network. Thus having more critical hours on a critical day is better for emissions reduction in New York State. For the fewer-hours case, although it has a lot of load reduction for the day, it is not favorable for NO_x reduction. This corresponds to peak load reduction shape. For this case, more load reductions are induced in very few critical hours. Thus the generators that are on the margin are no longer the dirtiest ones, rather more efficient ones. And also, due to the fact that the original critical hours may no longer set the capacity requirement of the system in this case, having too few critical hours in dynamic pricing scheme does not yield the best benefits. As for the base case with technology, although it has more load reduction during peak hours due to the steeper elasticity curve, it does not have as much overall load reduction because of the bigger demand increase in non-critical hours. However, this case is still quite instrumental in addressing the peak demand problem.

Table 3. Comparison of NO_x Reduction Using NCED Method

Scenarios	Base Case	More-Hours Case	Fewer-Hours Case	Base Case w/Tech
NY NO_x Reduction (tons/day)	6.7	7.1	5.1	5.6
NPCC NO_x Reduction (tons/day)	15.9	15.0	10.2	15.4
Daily Load Reduction (GWh)	28.8	27.6	26.9	21.2

This approach shows that DP programs can bring considerable reduction on a state level; Meanwhile, demand changes brought by DP programs in the New York State can also cause some emissions reduction or increase in other states nearby in the NPCC network, due to the interstate network links. Upon close examination, the emissions change in the neighboring states generally account for around 1% of their total emissions. In addition to considering how total emissions reduction can affect a state, the locality of emissions are also important, especially for metropolitan areas. The base case DP program produces 3.4, 1.2 and 2.2 tons NO_x reduction for NYC, LI, and ROS respectively, which accounts for 7.1%, 2.9% and 3.1% of original regional load. It is clear that there is more NO_x reduction in New York City. In addition to the fact that NYC is designed to have a few more critical hours than ROS and LI, it also shows that there are more peaking generators in NYC. As there's huge transmission congestion through the Central East and Upper New York to Southeast New York interface, a large portion of the peak demand needs to be served by generators local to New York City. DP programs prove a good way to solve peak demand problems in NYC, in terms of system reliability as well as regional air quality. They can also defer the need for new transmission build-outs to allow more efficient generation units to be dispatched across the state.

2.3.2.2 Emissions Reduction based on Targeted Replacement

2.3.2.2.1 Peaking Units Method

In this method, peaking units (PU) are identified by zone, thus NO_x reduction are evaluated by zone. It is assumed all peak load are served by those peaking units selected according to the criteria. As shown in Table 5, there are about 3 times higher NO_x reductions than in the NCED method. This is caused by the fact that the peaking units identified using the operating hour limits are among the dirtiest ones in New York States, especially in New York City and Long Island area. The generation-weighted average emission factors for NYC, LI and ROS peaking generators are 3.42, 5.85 and 0.80 kg/MWh, respectively. The selected peaking units are representative of peaking units in the zones, but it has the limitation of only covering a small portion of all generators. It is shown in figure 6 that although there is not as much overall load reduction in NYC as in ROS, more NOx reduction are produced in NYC, due to the high average emission factor.

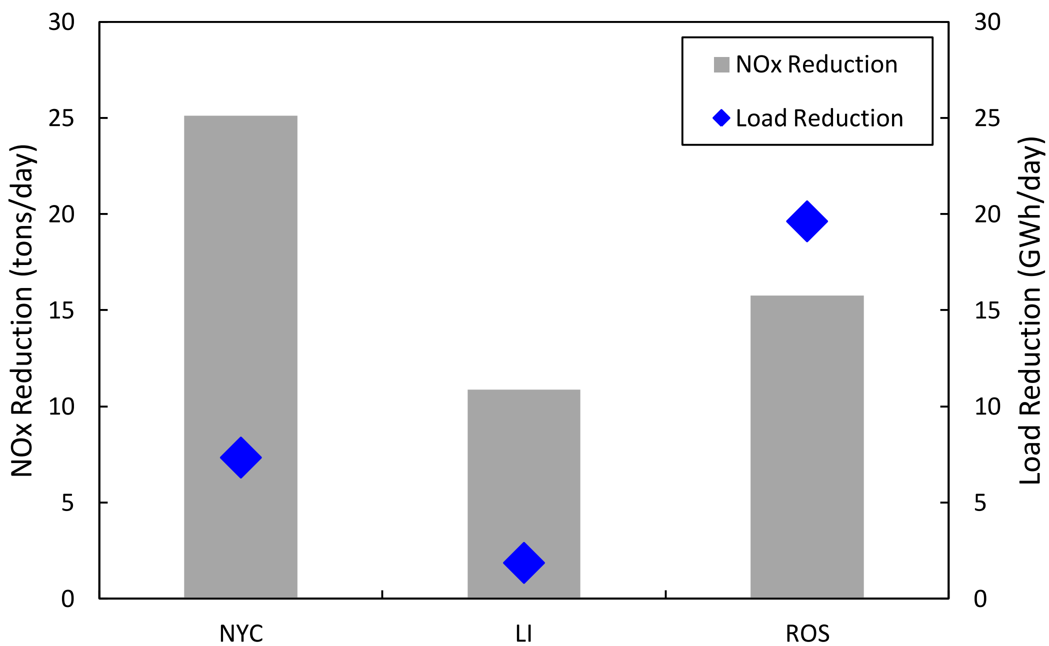

Figure 6. NO_x Reduction in Different Zones Using PU Method

2.3.2.2.2 Capacity Factor Method

With this method, DP programs yields the largest NO_x emission reduction among the proposed methods. First of all, by ranking generators according to capacity factors, those dirty and less efficient ones which operate at high fuel costs are selected. By examining the emission factors closely, it is obvious that the generators with lower capacity factors have larger emission factors than average.

Furthermore, the approach we adopted here is an extreme case because we consider all the dirtiest generators with very low capacity factors are fully dispatched to their total generation output within the simulated day. In the actual situation, for example, if a generator operates 6 hours totally in a year, it might occur in 1, 2, 3, up to 6 different hot days. In our simulation, we consider this generator is operated for 6 full hours in the simulated day, July 8th of 2008. This approach makes sure to get the upper bound of potential emissions reduction by dynamic pricing programs.

Most importantly, in the wholesale energy market, generators do not bid their total generations at a uniform price. The upper bidding block of clean generators can also get costly. Thus those generators with higher capacity factors can also be on the margin during peaking hours. However, in our approach which ranks the generators by capacity factor, this possibility is not taken into consideration. Therefore, the results of this approach are considered a maximum potential emissions reduction when dynamic pricing programs are implemented.

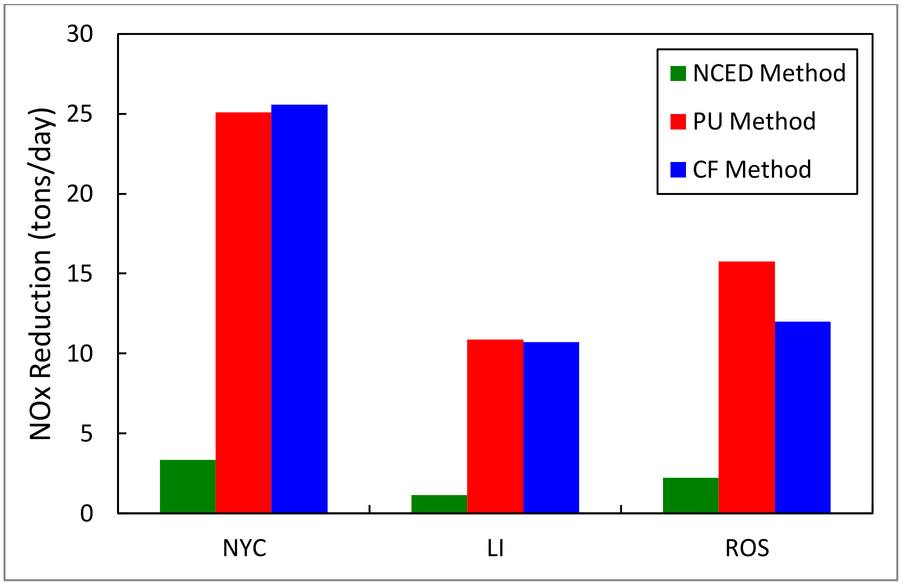

Figure 7. NO_x Reduction under Base Case DP program Using Different Methods

Figure 7 is a comparison of NO_x emission reduction using different methods under base case DP program. It is demonstrated that NCED method results in lowest NO_x emission reduction, while PU method and CF method produced highest NO_x emission reductions. Note that Figure 7 uses the CF method where each zone's load reduction is balanced by a commensurate decrease in supply located in the same zone.

2.3.2.3 Comparison of Emissions Analysis Methods

To better understand the maximum potential of emissions change under different dynamic pricing programs, in this comparison only load shaving are considered, assuming there is no load shifting. For the NCED method, emissions change from all states in the NPCC network were included to evaluate the total emissions reduction brought by implementing DP programs in New York State. For a meaningful variation on the CF method in Section *2.3.2.2*, Figure 8 is produced assuming peak load reduction within the entire NYS is balanced by a commensurate decrease in supply of the entire State, not constrained to any zone. Under this circumstance, the total NO_x reduction in New York State is larger than the previous case when demands has to be met by generators within each zone. The potential emissions reduction is bounded by CF method this way. On the other hand, it also demonstrates that having more transmission infrastructure to facilitate the power transmission between zones will greatly reduce emissions. For example, without any transmission congestion, when New York State load reduces, the dirtiest generators in NYC and LI would be first de-committed, incurring more emissions reduction.

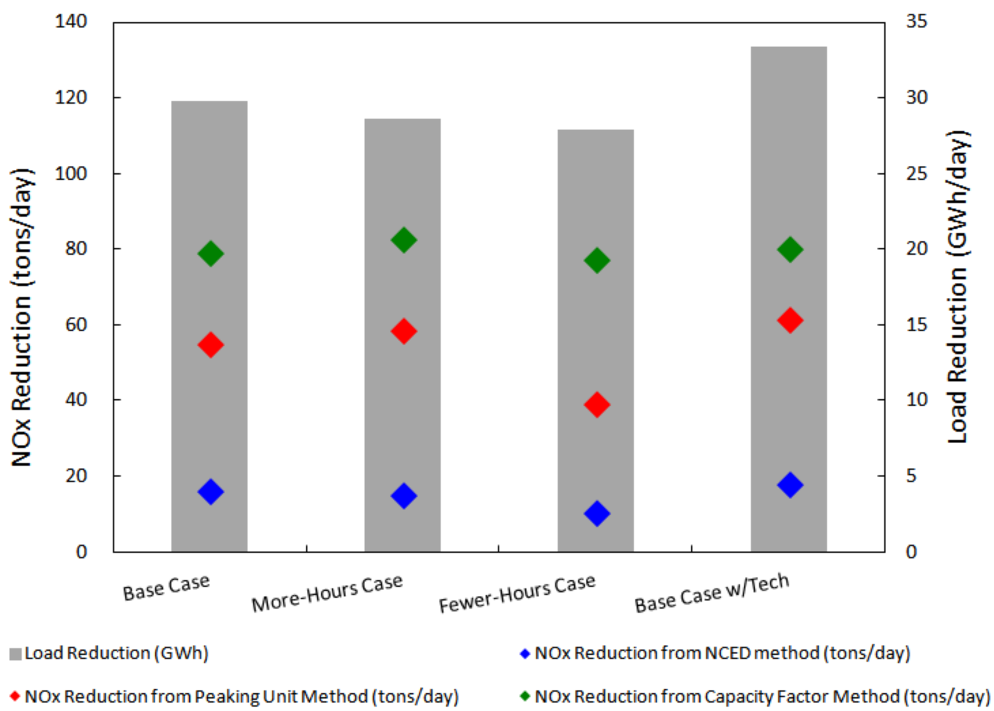

Figure 8. Comparison of Three Methods of Determining NO_x Reduction

Figure 8 shows that the emissions reduction is intuitively and positively correlated to the amount of load reduction for the base case, few-hours case and base case with technology. Interestingly comparing the more-hours case to the base case, the former has less load reduction, but more NO_x reduction. It is found for NYC and LI area, there is more load reduction for the more-hours case. However, for ROS there is less load reduction for the more-hours case—resulting in less total load reduction. Nonetheless, peakers' emission factors in NYC and LI are much higher than those in ROS—reducing emissions overall.

Figures 7 and 8 show that the NCED method may serve as a lower bound of emissions reduction, while the capacity factor approach may serve as an upper bound—reaching to about five times of the NPCC total emissions reduction using NECD method. Estimation from the peaking units approach sits in-between, because this method results in a partial selection of dirty units. In comparison, the CF method captures a larger pool of dirty units.

2.4 Implications and Limitations

With the emerging problems brought by growing peak demand in the summer, dynamic pricing serves as a good solution to improve the system reliability by reducing peak demand and to improve regional air quality by reducing emissions from power plants. In this study, impacts of dynamic pricing programs are evaluated through a multifaceted approach.

Four scenarios of dynamic pricing programs are discussed to better understand the difference in dynamic retail electricity rate designs. Through analyzing the demand reduction for the system, it is shown that dynamic pricing programs can greatly reduce hourly peak demand on hot summer days, up to 23% for critical peak hours. Thus DP programs enhance the system stability and reliability.

Three approaches are proposed in this study to evaluate the impact of dynamic pricing on emissions. Firstly, an MATPOWER based approach is performed. The emissions are evaluated based on the network-constrained economic dispatch in the Northeast region as a whole, including New York. It yields around 7 tons NO_x reduction in New York State, and some reductions outside of New York. The result shows DP programs are effective in inducing NO_x reductions, but are still far from the New York goal of 50.8 ton NO_x reduction per day. In the peaking units method, the NO_x reduction reaches about 50 to 60 ton per day, which reaches the goal. This is a large amount of NO_x reduction just by implementing DP programs. Furthermore, in the extreme case of capacity factor method, the NO_x reduction can reach 80 tons, exceeding the goal by around 60%, and serves as the upper bound of possible emissions reduction that can be reached. The proposed methods demonstrate that while dynamic pricing programs can achieve solid NO_x reduction, there is still large potential to further reduce the NO_x emissions by implementing DP programs, especially when paired with upgrading or addition of the transmission infrastructure.

The emissions estimation has some limitations: Firstly, MATPOWER includes a reduced network of NPCC. Some generators are aggregated, and some are not included. So the estimation from NCED method might be lower than the actual condition. Also, EPA includes generators that have 200 MW or more generation capacity. Smaller units are omitted from the inventory. Incomplete inventory will affect the accuracy of average emission factor and the emissions changes. There might be other smaller, dirtier or cleaner units whose emissions are not captured by our methods. Lastly, for the capacity factor approach, information on generator costs is not available to the public. For example, cleaner units such as combined cycle gas units can also be on the margin in peak hours. Thus this method yields an upper bound of the potential emissions reduction. All in all, this study estimates the emissions benefits that can be brought by dynamic pricing by bounding the uncertainties, and has demonstrated that dynamic pricing has the potential to produce substantial NO_x reduction in New York State.

CHAPTER 3

EMISSIONS MODELING

3.1 Introduction and Methodology

As electricity use is still growing with the economic development, emissions from electricity production will still be a problem in the future. Some analyzed the linkage between consumer lifestyle, energy use and CO_2 emissions from consumers' perspective, pointing out the importance of studying consumer choices for policy makers [30-32]. Dynamic pricing, as one of the major ways to engage customers in the electricity market, will thus impact the emissions and air quality due to energy consumption. Without emissions modeling, it is hard to visualize the overall air quality impacts. The methodology of this study is shown in Figure 9.

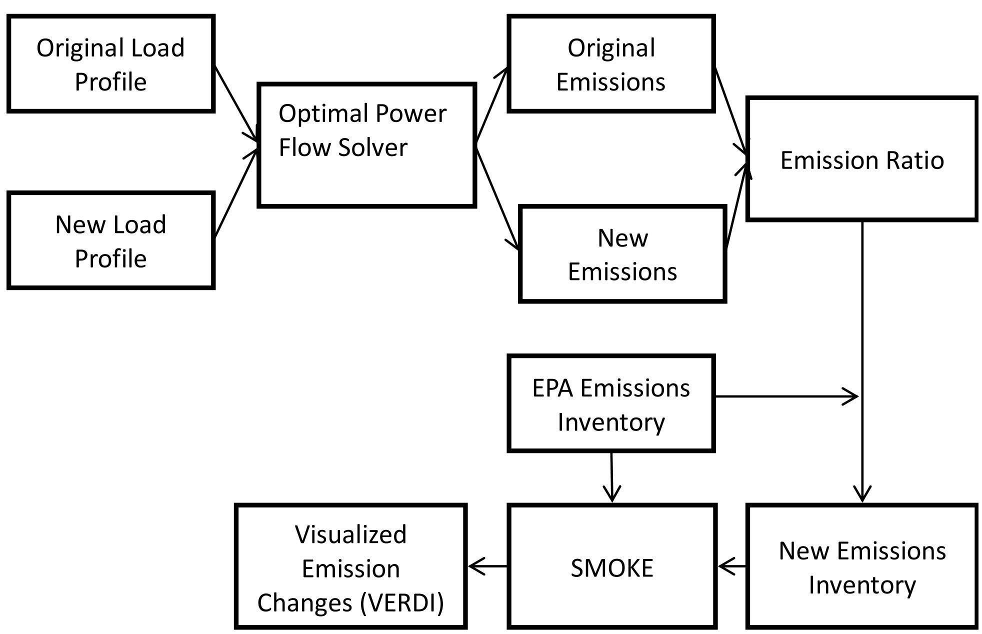

Figure 9. Methodology of Emissions Modeling

Sparse Matrix Operator Kernel Emissions (SMOKE) [33] modeling system is used for processing emission inventory data to prepare formatted emission input files for the Air Quality Models, including Community Multi-scale Air Quality Model (CMAQ). CMAQ is a three-dimensional gridded atmospheric chemistry and transport modeling system, using coupled mathematical representations of actual chemical and physical processes to simulate air quality [34]. The results of emissions analysis under the dynamic pricing schemes could be used in evaluation of air quality, and decision-making about emissions controls and generation dispatch for both urban and regional applications. The impacts of dynamic pricing schemes on air quality could be evaluated using CMAQ in further studies.

3.2 Emissions Processing

There are 4 emissions categories in SMOKE: area sources, mobile sources, point sources and biogenic sources. While biogenic sources are currently integrated with the air quality model in CMAQ, emissions from other sources are processed and integrated in SMOKE.

3.2.1 Area Source Emissions Processing

Area sources include two categories: nonpoint/stationary area sources and non-road mobile sources. Nonpoint/stationary area sources refer to emissions that spread over a spatial extent and are not movable, not possible to collect at each point of emissions. Examples of nonpoint/stationary area source emissions include residential heating, use of paints and varnishes. Non-road mobiles sources are considered to be vehicular or other movable sources that do not travel on roadways, such as lawn mowers and constructions vehicles. There are several sub-categories in the area source emissions inventory, thus all of them need to be combined into one area source output file.

(1) afdust: It refers to area-source fugitive dust. This sector contains PM_{10} and $PM_{2.5}$ emission estimates for nonpoint SCCs identified as dust sources, such as paved/ un paved roads, construction, agriculture production and mining.
(2) ag: It refers to agricultural NH3 sector, including livestock and fertilizers
(3) c1c2rail: It refers to locomotive and Class 1 and 2 CMV (commercial marine vessel) emissions, except for railway maintenance locomotives.
(4) nonpt: It refers to the main set of stationary nonpoint source emissions from the NEI(National Emissions Inventory).
(5) nonroad: It refers to monthly exhaust, evaporative and refueling emissions from nonroad engines.
(6) othar: It refers to other area emissions than those in the U. S. state-county geographic FIPS, e.g., that in Canada and Mexico.
(7) othon: It refers to other onroad mobile sources from Canada and Mexico.

Gridded area emission file of the above subcategories are merged into area source emissions using Mrggrid program in SMOKE. A file list containing these logical file names is also created as an input into Mrggrid.

3.2.2 Mobile Source Emissions Processing

Mobile source emissions refer to emissions from motorized vehicles that travel on roadways, such as light-duty gasoline vehicles, heavy duty diesel vehicles. They are 3 types of mobile emissions in the gridded emissions inventory:

(1) on_noadj: It refers to monthly on-road emissions that are not subject to temperature adjustments.

(2) on_moves_runpm: It refers to on-road running mode emissions that contain different temperature adjustment curves from cold start exhaust.

(3) on_moves_startpm: It refers to on-road cold start mode emissions that contain different temperature adjustment curves from running exhaust.

In addition to on-road emissions, which mainly refer to running exhaust, crankcase running exhaust, brake/tire wear, or on-road evaporatives, there is also off-network emissions in the mobile emissions category, such as parked engine-off, engine starts, and idling. Motor Vehicle Emission Simulator (MOVES) [35] is thereby used to process mobile emissions. Specifically, the SMOKE-MOVES integration tool combines MOVES with SMOKE, to provide meteorological data and MOVES-based emissions rate. Eventually the output of MOVES is integrated with SMOKE for modeling on-roadway emission processes and off-network emissions processes, to create hourly gridded speciated model-ready emissions input for CMAQ.

3.2.3 Point Source Emissions Processing

Point source emissions are those that can be identified by a specific geographic coordinates, such as an individual facility. It is further subdivided into 3 sources as following:

(1) pt: It refers to emissions from electric generating utilities(EGUs).

(2) ptnonipm: It refers to emissions from remaining non-EGUs.

(3) othpt: It refers to all non-US point emissions, such as that from Canada, Mexico and all other offshore emissions.

Dynamic pricing programs will affect electric generation in the power plants, thus the first type of emissions “pt” is the main focus of this study.

3.2.4 Point Source Emissions Modeling and Simulation

Point source emissions processing converts hourly emissions to hourly, gridded model-ready emissions of the chemical species used by air quality models. In this study a CMAQ-based approach is performed. The processing steps are shown in Figure 10:

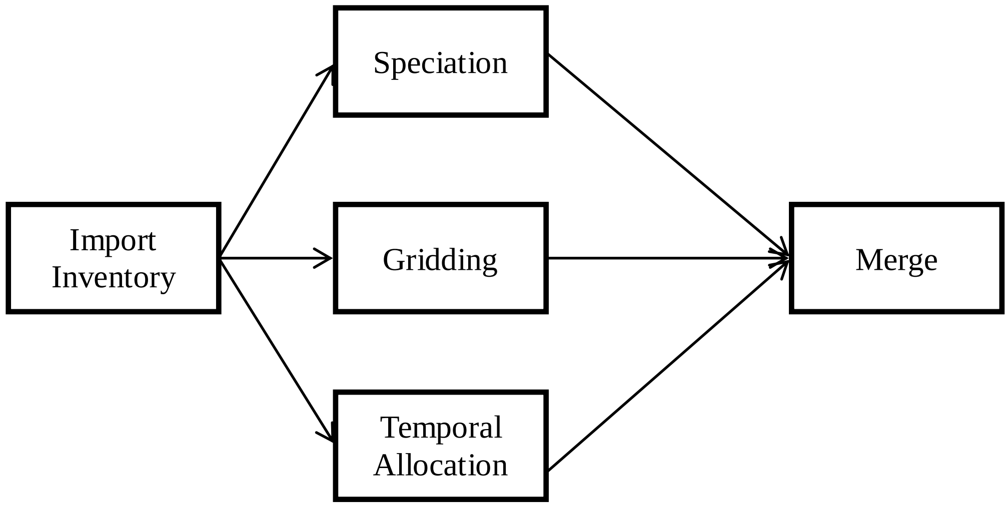

Figure 10. Point Source Emissions Processing Steps for CMAQ-based Approach

Emissions modeling requires spatial, temporal parameters and emissions inventory as input information. The model grid used in this study is named 12US1. It has 459 columns and 299 rows, and each grid cell's size is 12 by 12 kilometers. The specification is shown in Table 4:

Table 4. Spatial Domain 12US1

Projection	Lambert Conformal Conic
Standard Parallels	33^{0}, 45^{0}(N)
Ion/ Lat Projection Center	-97^{0}(W), 40^{0}(N)
Domain Origin(From Projection Center, in km)	-2556(W), -1728(S)
Horizontal Grid Spacing	12 km
Horizontal Grid Count(x,y)	459, 299

The vertical resolution is 15 layers. The episode for this emissions modeling is one full day in the summer of 2008. The duration is 25 hours. Point sources emissions are printed by vertical layer and by hour. A typical summer day, July 8th, 2008 is modeled to demonstrate the emission changes under different dynamic pricing schemes.

The Continuous Emissions Monitoring (CEM) hourly-specific data from U.S. Environmental Protection Agency inventory (EPA) website is used for EGU point source emissions inventory [41]. Evaluation is focused on NO_x and SO_2 emissions. NO_x is the major catalyst for the formation of ozone, and SO_2 is the precursor to acid rain and atmospheric particulates that are very hazardous to human health. To investigate the relationship between emissions from each power plant and the implementation of dynamic pricing programs, an optimal power flow simulation tool is needed to convert the zonal energy usage to unit-level power production from the generators.

To link the simulated emissions change in the simplified NPCC network with potential emissions change based on historical data, an emission multiplier f is assumed to represent the ratio of original emissions to DP case emissions.

Firstly, we run the original-load case in the NPCC network using MATPOWER, and get the original emissions rate. Then we run the DP cases in the same network setup, but with the load after implementing dynamic pricing programs, and thus get the DP case emissions rate. From these simulations, we can assume that generators in the NPCC network will respond in such ways like reducing/ increasing power output when load reduction/ increase occurs, and that the emissions from the generators will decrease/ increase as a result. Emission multiplier f is the ratio of the DP case emissions rate versus original emissions rate. It is thus used to represent the emissions change pattern of the generators in the network. This is illustrated in the first part of equation 9. Then f is applied to the historical emissions in the CEM inventory to simulate how the power re-dispatch would have changed the historical emissions. The product of the ratio f and the historical CEM emissions rate equals the expecting CEM emissions rate, if dyanamic pricing programs were implemented at that time. Equation 9 illustrates how the assumption is built and applied to the emissions inventory.

$$f = \frac{DP\ Case\ Emissions\ Rate}{Original\ Emissions\ Rate} = \frac{Expecting\ CEM\ Emissions\ Rate}{Historical\ CEM\ Emissions\ Rate} \tag{5}$$

The key of Equation 5, f is calculated using the NO_2 and SO_2 emissions rate from MATPOWER output. During peak hours when there is emissions reduction from the generators, f is smaller than 1; during off-peak hours when there is emissions increase, f is bigger than 1. After applying emission multiplier f to emissions from the same generator in the CEM emissions inventory, we can get the expecting emission rates based on historical emissions with the implementation of the dynamic pricing programs.

From MATPOWER output emissions to emissions inventory for SMOKE input, there is a generator matching process from the generators in the NPCC network to those in the Eastern Interconnection network, and to those in CEM data. The generator names, ORIS and boiler codes are used to identify each generator, and to match with the generators in different networks. And this process will have impacts on the effectiveness of emissions change in the CEM inventory.

There are 3 main factors that affect the effectiveness of emission changes. First and foremost is to match the generators. Generators in the NPCC network, which is used in MATPOWER, should be matched to generators in EPA, which is used in CEM inventory. This matching contains two parts. On One hand, the generators from MATPOWER are identifiable by their names. However, generators in the CEM inventory is identified by their ORIS ID and boiler ID. In order to match the generators in these two emissions inventory, the Eastern Interconnect inventory is introduced here. So generator names in the NPCC network needs to be matched with generator names in the Eastern Interconnect inventory. On the other hand, ORIS ID and boiler ID of the generators found in the Eastern Interconnect inventory are used to match with that in the CEM inventory. About 45% of the generators in the NPCC network can be matched during this step.

Then after the generators are matched, EPA inventory should have valid data on this specific generator. Invalid data in the EPA inventory is another possible cause of not reflecting the emission changes in the new emissions inventory. Any “missing” data are provided with a “-9” value to indicate the information was not available. And records that represent hours during which units were not operating are not included in the inventories to make them smaller. The above two factors resulted in a 25% effectiveness of emissions change in the EPA emissions inventory.

However, there is another factor that we need to take into account of. For some generators that actually have emission changes, if the original emissions output are negligible, then the emissions ratio f would not accurately reflect the emission changes. For example, when abnormally large emissions ratio occurs, e.g. when the ratio is larger than 10, it usually occurs to those generators that has very minimal emissions output. Under this circumstance, even though the emissions ration is very large, the absolute emissions change on this particular generator is still negligible. Upon examining these low-emission generators, a filter is set for the data processing to eliminate abnormal emissions ratios. If taken this factor into consideration, the expecting effective number of hours that has emission changes is further reduced.

Lastly, not all generators in the NPCC network are affected when the electricity demand in a region changes. The emission ratio of original emissions to DP emissions will be almost 1 if the Optimal Power Flow (OPF) solver does not re-dispatch the power production on this particular generator.

In addition, it is found during the generator matching process between these emissions inventories that there are generator units in the NPCC network with exact same names, not even numbered differently. In fact, they should be different boilers at the same facility. Thus in the matching process, when generating units with same names occur, they are successively assigned to different units under the same name in the Eastern Interconnect inventory, to match to different units in CEM inventory. It means they keep the same ORIS ID, but were assigned with different boiler ID. This effectively avoided repeated emission changes on one unit during the matching process.

3.3 Results and Discussion

After the emissions inventories are processed by SMOKE, the result is viewed and analyzed using Visualization Environment for Rich Data Interpretation (VERDI) [36]. VERDI is a java based program for visualizing multivariate gridded environmental modeling datasets. The purpose of using VERDI is to demonstrate the aggregated dynamic pricing emissions reduction horizontally by its location and vertically by layer. VERDI provides a GUI that makes it easy to import the datasets, creating formulas, and generating plots that meet our needs. Figure 11 and 12 includes the time series plots for NO_x and SO_2 reduction in layer 6 on a typical summer day, July 8th, 2008. The time series plots show the average emissions change across the modeling domain over the course of a day.

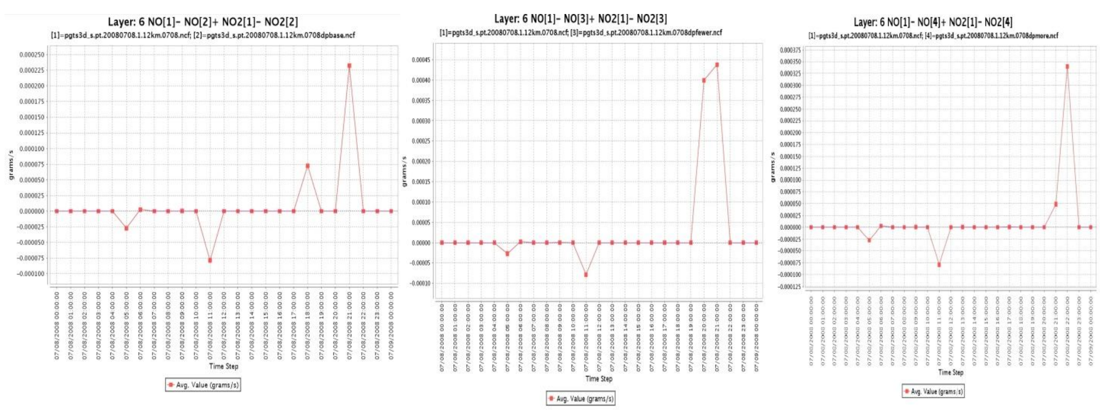

Figure 11. Average NOx Emssions Reduction on a Typical Summer Day

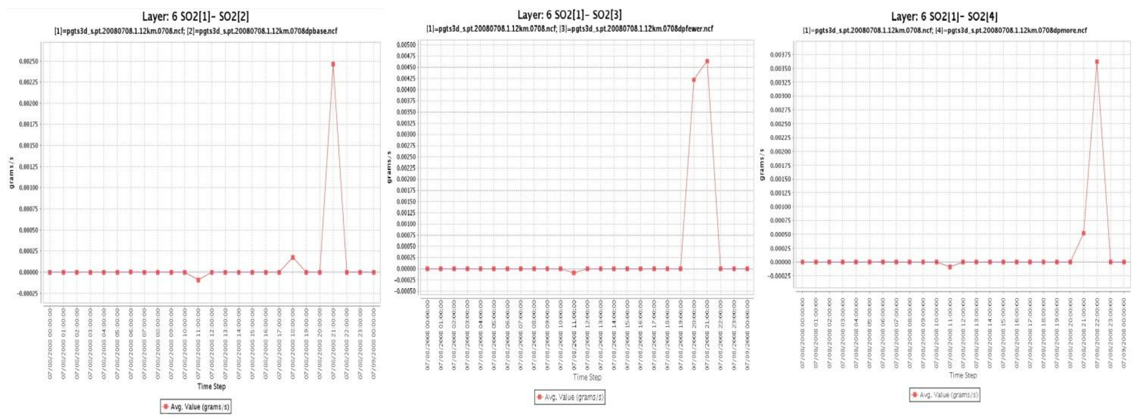

Figure 12. Average SO_2 Emssions Reduction on a Typical Summer Day

Layer 6 is selected from the 15 modeling layers to be presented here as it is a layer where the most emissions change occurs. One thing to be noted is that it is set to use Coordinated Universal Time (UTC), for consistency purpose with the format of meteorology data and future air quality analysis in CMAQ. Since NPCC region are in the Eastern Time zone, what to be investigated is 5 hours behind what is shown in the figure. That is also why no emission changes are observed before 5 am.

The plots are made for the formula in the headings, which represent the NO_x/ SO_2 emissions difference in the unit of gram/s between the original case and the DP cases. The NO_x emissions reduction includes emissions change in the form of NO as well as NO_2. The graph in the left represents DP base case, the graph in the middle represents DP fewer-hours case and the graph on the right represents DP more-hours case.

Not surprisingly, the graphs of NO_x and SO_2 emissions reduction in Figure 11 and 12 are similar in shape. It is shown in these plots that the emissions reduction in layer 6 is negative in the morning, which means there is emissions increase during early morning, which are off-peak hours. It is caused by the load-shifting effects of the DP schemes. Customers reduce their energy consumption during critical hours when electricity prices are high, and then increase energy consumption during non-critical hours when the prices are low. Meanwhile, in each case there is considerable emissions reduction in the afternoon, which is always peak time of the day. Layer 6 is a selected layer with major emissions change out of the 15 layers, and it is a good indication of the overall emissions change across the entire domain. The emissions reduction pattern coincides with the load change shapes in Section 2.3.1. In addition, by close examination at the y-axis limits in Figure 11, it is clear that DP fewer-hours case has the maximum single hour emissions reduction among those 3 cases. And it occurs in 21 o'clock, meaning 16 o'clock in the afternoon in Eastern Standard Time.

What's more, tile plots of the modeled emissions are included here to display grid cell aggregated data through time steps and vertical layers. The y axis limits are set to be the same between different DP cases for comparison convenience, in which case, the color on the map can demonstrate the value of the emissions reduction, as the value can also be easily compared from one case to another.

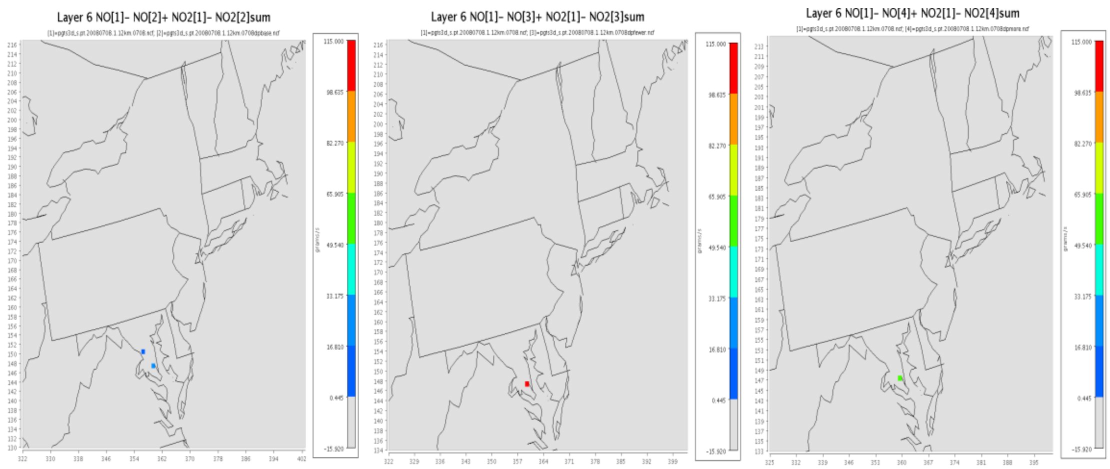

Figure 13. Total Daily NO_x Emissions Reduction in DP Cases

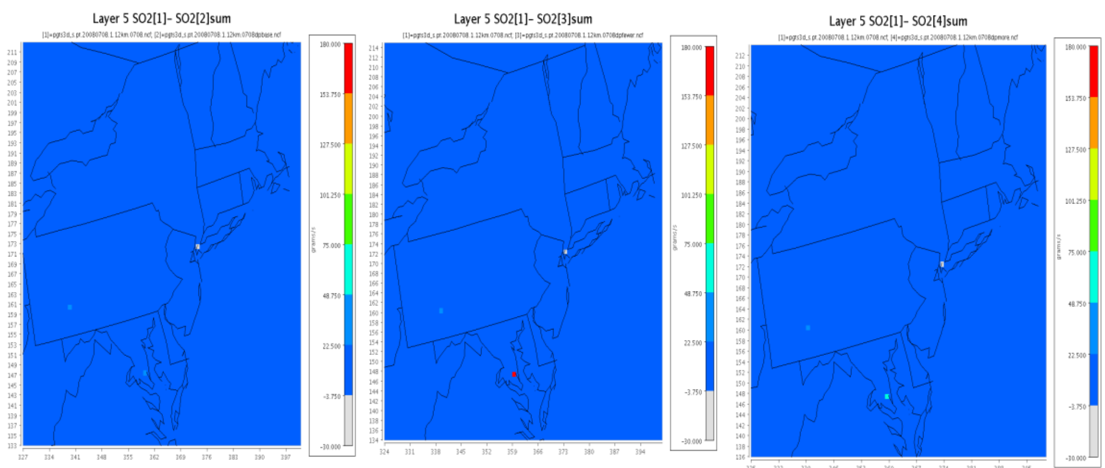

Figure 14. Total Daily SO_2 Emissions Reduction in DP Cases

Figure 13 and 14 illustrate the total emissions change over the course of the day between the original case and the DP cases. Seeing from Figure 13, there's NO_x reduction in Maryland, ranging from around 110 grams/s in DP fewer-hours case to around 15grams/s in DP base case. Figure 14 shows SO_2 reduction in Layer 5. Layer 5 is also a layer where considerable emissions change occurs. It is seen that there is notable SO_2 emissions reduction in the Indiana county of Pennsylvania as well as in the Maryland area. The y axis limits are carefully adjusted so that the graphs also reveal there is a little SO_2 emissions increase in the NYC area.

However, the tile plots of total emissions reduction is partly biased because by default VERDI displays the time in UTC. So the total emissions reduction calculated here does not take into account the last 5 hours of the day. To better conclude on the emissions change, a closer look is taken at the emissions change from the power systems model. The tracing back of emissions reduction from the generator units shows that there is considerable emissions reduction in 20 p.m. in Queens County and also on 23 p.m. in Richmond County, New York. Since the emissions reduction occurs after the time step 25 in UTC, it is not captured by the tile plots discussed here, although it actually happens on the same day in Eastern Standard Time. The other states in the NPCC network are less affected, due to the fact that we are modeling DP programs in NYC, and that the MATPOWER NPCC model captures more generators in New York State.

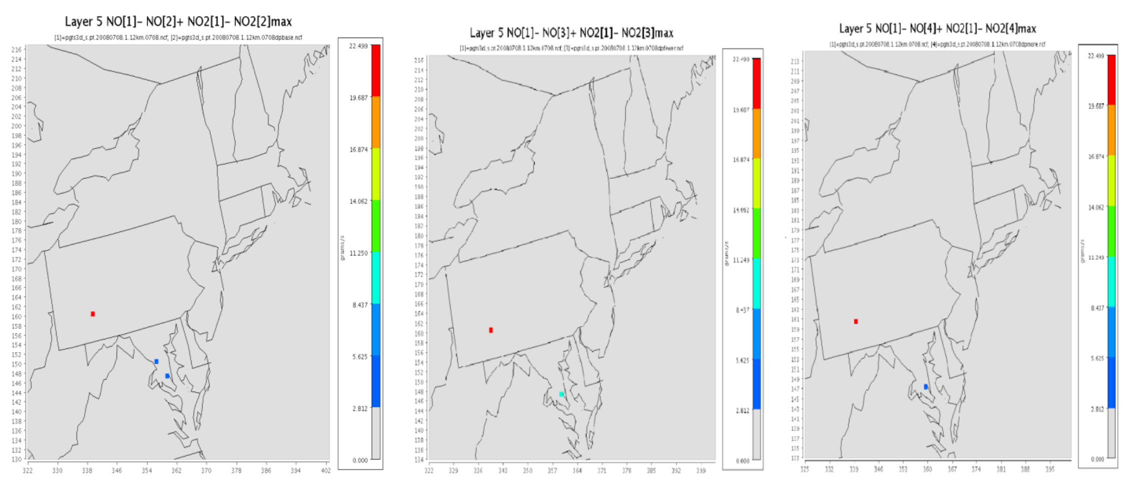

Figure 15. Maximum NO_x Emissions Reduction in Layer 5 in DP Cases

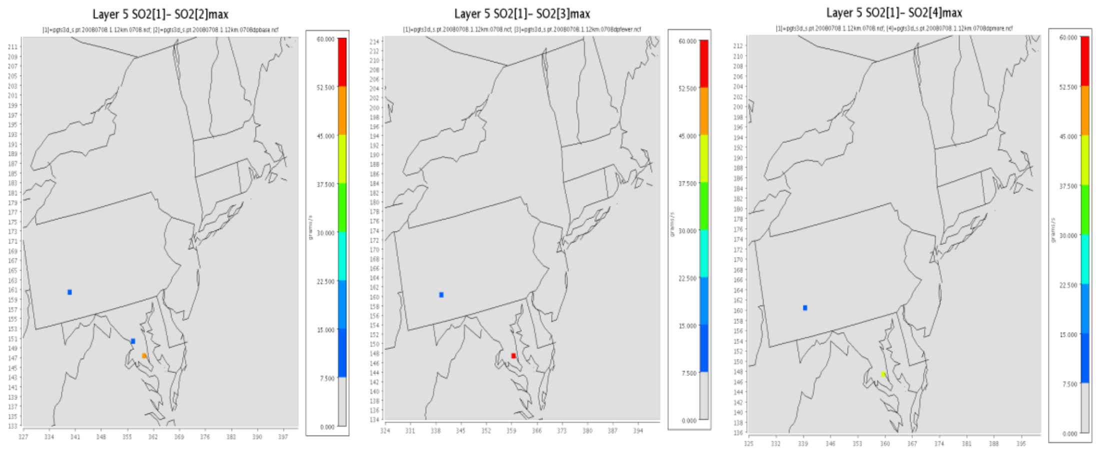

Figure 16. Maximum SO_2 Emissions Reduction in Layer 5 in DP Cases

Figure 15-18 show the maximum emissions reduction between the original case and the DP cases over the course of the day in layer 5 and layer 6, respectively. Aside from further demonstrating that DP fewer hours case has larger maximum emissions reduction than DP base case and DP more hours case, it also provides a good example for comparing NO_x and SO_2 emissions reduction in different layers. It is evident from the y axis limit that there is more emissions reduction in layer 6 than in layer 5 for both SO_2 and NO_x. Also, there is more SO_2 reduction than NO_x reduction, especially in layer 6.

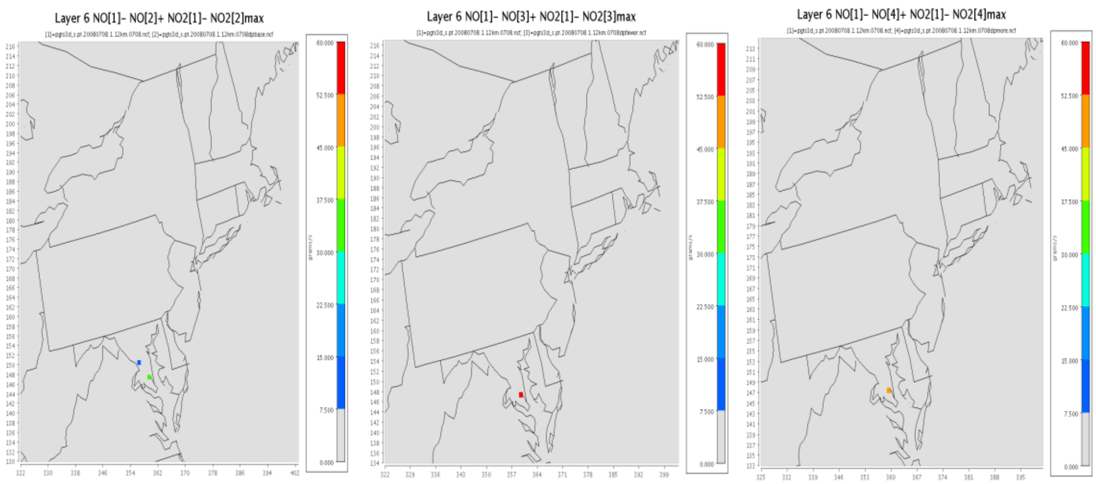

Figure 17. Tile Plots of Maximum NO_x Emissions Reduction in Layer 6 in DP Cases

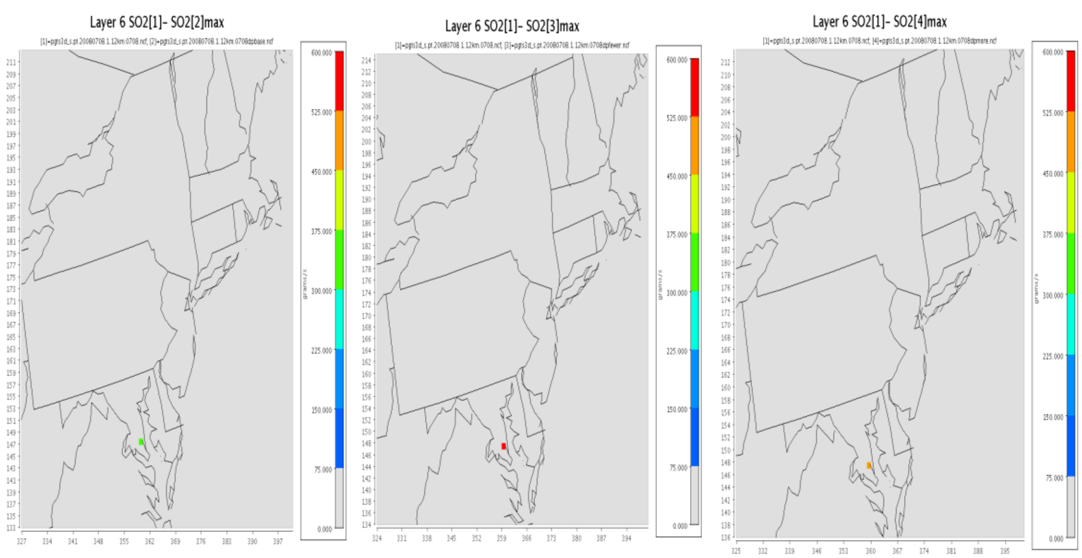

Figure 18. Tile Plots of Maximum SO_2 Emissions Reduction in Layer 6 in DP Cases

Given that NO_x and SO_2 are very harmful to human beings, emissions control is very important for urban and metropolitan area like the NYC and Washington, D. C., as well as the adjacent New Jersey state with high population density. Since future environmental regulations will ultimately affect generation resources in New York State, the result of this study will be useful in policy making and regional resource planning for the government. Further study in assessing dynamic pricing is to simulate the air quality impacts in CMAQ model. As the various emissions interact with each other, pollutant such as ozone, fine particulate matter and volatile organic compounds will occur, thus imposing adverse influence in human's everyday life and lifespan. Moreover, when combined with various meteorology conditions, emissions from one place will not only influence the local air quality, but also travel and influence air quality of places far away. Consequently, combining power system model with emissions and air quality model is very important in evaluating the expecting environmental impacts of power generation, which in turn will affect the power dispatch and transmission infrastructure in the future, if environmental cost is taken into consideration.

APPENDIX A

PRICE MODELING

Energy charge tracks Locational-Based Marginal Prices (LBMPs) set in the New York Independent System Operator (NYISO) day-ahead wholesale electricity market. Flat energy charges vary monthly, depending on the weighted average hourly prices during each month. Therefore, the hourly load shape is needed for the representative classes. We use load profiles from utility companies to represent customers in different regions, Consolidated Edison (ConEd) for customers in New York City and Long Island, and Niagara Mohawk (NiMo) customers in the rest of state (ROS). There are 11 zones in the New York state, Zone A to Zone K. New York City is in Zone J, while Long Island is in Zone K. In NYISO's wholesale electricity market, hourly load and price data is posted by zones [37]. In general, SC-1 class of customer is used for the residential class and SC-2 customer class is used for commercial and industrial classes. For ConEd, the day type (such as Monday, Sunday, Holidays) and the temperature on that day are used to match the day with certain hourly load shapes [38]. For NiMo, we still use SC-1 standard service type to represent residential class, and use the weighted average load of SC-2 demand and SC-2 non-demand to represent commercial and industrial (C&I) class [39]. It is weighted by the energy consumed by the demand and non-demand class respectively, which can be found in the annual FERC Form 1 filed by Niagara Mohawk [40]. The energy charge for flat rate is calculated as following:

$$Energy\ Charge_{class,month} = \sum_{hr \in month} \left(LBMP_{hr,class} \frac{load_{hr,class}}{load_{month,class}} \right) \quad \text{(A1)}$$

Dynamic energy charges vary on an hourly basis. Hourly LBMPs are used as the energy cost component in the dynamic electric rate. This way, the spot price in the wholesale market is passed through to the retail rates.

Capacity is a proven ability of a resource to generate power. Capacity charge is calculated based on the annual price of Unforced Capacity (UCAP), adjusted by Installed Reserve Margin (IRM), Equivalent Forced Outage Rate on demand (ERORd), Load Factor (LF) and locality. UCAP is transacted in NYISO-administered ICAP auctions. The price of UCAP is determined by automated auctions. There are 3 types of auctions including strip auction, monthly auction and spot auction, conducted separately for 3 capacity control areas: NYC, Long Island and NYCA.

LF is the rate class's average load divided by peak load in the load profile we get from the representative utility companies. Local reliability rules require LSEs in Zone J (New York City) and Zone K (Long Island) to procure minimum level of capacity from facilities that are located in their zones.

$$Capacity\ Rate = \frac{P_{ROS}\ UCAP}{8760\ LF_{ROS}} + \ Local\ Premiu \quad \text{(A2)}$$

$$Local\ Premium\ in\ Zone\ J\ or\ K\ = \frac{LCR(P_{J\ or\ K} - P_{ROS})(1 - EFORd)}{8760\ LF_{J\ or\ K}} \quad \text{(A3)}$$

$$UCAP\ =\ (1 + IRM)\ (1 - EFORd) \quad \text{(A4)}$$

P_{ROS}, P_J, and P_K denote the price of UCAP in the region. UCAP shows a proven output of generating units, adjusted by availability and deliverability.

Availability is affected by derating factors, such as forced outages, derate, and actual performance, represented by EFORd here. Forced outage and derate affect availability in different ways. For example, if EFORd is 0.05 due to forced outage, then the generating units is available 95% of the time, with full power output. If EFORd is 0.05 due to derate, then this generating unit is available all the time, but with 95% power output.

The IRM for the New York Control Area (NYCA) is established by New York State Reliability Council (NYSRC), such that the probability of disconnecting any firm load due to resource deficiencies shall be not more than once in ten year. The NYISO establishes Load Serving Entities (LSE) installed capacity requirements, including Locational Capacity Requirements (LCR), in order to meet the statewide IRM Requirements.

The NYISO uses UCAP to match buyers and sellers, i.e., the LSE obligation to buy, and the amount each generator can sell into the capacity market. UCAP is transacted in NYISO-administered ICAP auctions. The price of UCAP is determined by automated auctions. There are 3 types of auctions including strip auction, monthly auction and spot auction, conducted separately for 3 capacity control areas: NYC, Long Island and NYCA. Strip auction is also called capability period auction, and it is run at least 30 days prior to the start of the capability period. There are two capability periods: winter capability period is from November to April, and summer capability period is from May to October. Strip auction solves for a 6-month strip of UCAP at a single price per month. The monthly auction is run at least 15 days prior to the start of the month, and capacity may be bought or sold for any month remaining in the capability period. The clearing price is the weighted average price of any MW that is sold in this auction. For example, in the monthly auction for May, the capacity for May, June, up to October can be transacted. On the other hand, in the monthly auction for October, only capacity for October will be transacted. The spot auction is run 2 to 4 days prior to the start of the month, and capacity is only sold for the upcoming month. It must certify all capacity before auction.

For the capacity charges in flat rate, the capacity cost is allocated evenly to each hour of the year; while in the dynamic rate, it is allocated only to the peak hours. During peak hours, which is defined as approximately top one percent of demand hours in base case, dynamic electricity prices greatly increase due to additional allocation of capacity costs. On the other hand, during the other hours of the year, it presents a lower price than flat rate. This would send stronger price signal to the customer and thus encourage greater response when needed the most [41]. In addition to the base case, we have two more cases to consider: base case with technology and more-hours case with technology. In these cases, we assume elasticity is high with enabling technologies. In the latter case, we design the case with more critical hours, and also with high elasticity due to enabling technologies. The purpose is to flatten the load shape, instead of creating two sub-peaks while cutting the critical peak. Considering this reason, the fewer-critical-hours case is not favorable. If we cut the critical hours by half, the load shape will change in an undesirable way, i.e., the hours on the two sides are likely to become the new peaks that will be setting the capacity requirement. Thus the load response is wasted on hours that no longer set the capacity requirement.

Other charges represent non-generation charges such as transmission, distribution and other tariff elements. It stays the same for flat and dynamic rates. Other charges vary by class and by utility companies. Typical customer bills for residential, commercial and industrial customers are available from New York State Public Service Commission website [42]. Since monthly service charge does not affect consumption decisions under flat rates or dynamic rates, it is deducted from the total delivery charges on the bill. Then we calculate the mean of other charges by different customer size in each customer class. As commercial and industrial customers are considered as a whole in this study, we need to integrate the other charge for these two classes. Energy sales data for the two utility companies is available from the US Energy Information Administration (EIA) website [43]. Then we take a weighted average of the commercial and industrial charges to get the other charges for the representative SC-2 class.

APPENDIX B

COST EVALUATION

Customer costs are calculated assuming that all customers are given market electric prices without long-term contracts. Since other charges stay the same from original case to dynamic pricing cases, energy cost and capacity cost caused major changes in customer costs. The costs per time period are calculated as the following.

$$Original\ Energy\ Cost = Flat\ Energy\ Price * Original\ Load \tag{B1}$$

$$Dynamic\ Energy\ Cost = LBMP * Dynamically\ Priced\ Load \tag{B2}$$

$$Original\ Capacity\ Cost = Original\ Capacity\ Price * Load\ for\ All\ Hour \tag{B3}$$

$$Dynamic\ Capacity\ Cost = Adjusted\ Capacity\ Price * Load\ for\ Critical\ Hours \tag{B4}$$

From calculations based on the Equations B1 to B4, dynamic pricing will incur savings on energy costs, but higher capacity costs for the summertime, for annual capacity costs for the original case will be collected solely during critical peak/summer hours for the DP cases. For the base DP case, the benefit from energy cost savings is 230 million ($2008), which is 3.58% of the original energy cost. On the contrary, there is a 1.2 billion ($2008) increase in capacity costs. Overall, there will be a customer cost increase by 7.45% during the summertime.

The cost increase is resulted from the high capacity price during the critical hours. In the dynamic pricing case, capacity charge is only applied to the critical hours, whose load tops the whole summer. What's more, the capacity charges in critical hours in dynamic pricing cases are about 100 times that of the original case, because the total capacity charge is only distributed to the critical hours (60~90 hours) as opposed to all hours (8784 hours) in the year. Thus the capacity cost savings in the rest of the days of the summer is not enough to cover the capacity cost losses in the critical hours in the summer. This is the reason why there is cost increase for the customers in dynamic pricing cases from June to September. From the consumer perspective, there may be significant inertia to them enrolling in utility pricing programs when total electricity bills will be higher than what they have been paying particularly for the costliest summer months.

However, if dynamic pricing programs remain active for the whole year, customers will likely save on electricity bills, because they will benefit from zero capacity cost for the non-summer months. In effect, customers will only pay energy costs, which are shown to decrease in DP scenarios. Furthermore, evidence of monthly bills with PG&E and Alabama Power rate schedules also shows that with DP programs, customer bills increase during summer and decrease in other months of the year [44]. Meanwhile, the utilities will have major capacity costs savings from DP programs during summer, which will eventually pass on to the retail customers. Table 5 lists the cost changes from the flat rate to dynamic rate in the four cases studied.

Table 5. Comparison of Customer Costs

	Base Case	Fewer-Hours	More-Hours	Base-Tech
Flat Energy Cost ($MM, 2008)	6420	6420	6420	6420
Dynamic Energy Cost ($MM, 2008)	6190	6200	6180	6440
Energy Cost Diff ($MM, 2008)	230	220	240	-20
Flat Capacity Cost ($MM, 2008)	441	441	441	441
Dynamic Capacity Cost ($MM, 2008)	1660	1710	1690	1590
Capacity Cost Diff ($MM, 2008)	-1220	-1270	-1260	-1140
Customer Saving ($MM, 2008)	-788	-837	-816	-1100
Cost Increase (%)	7.5	7.9	7.7	10.5

Under dynamic pricing scheme, all of the cases will incur energy cost savings for the customers. In terms of energy costs, the impacts of the four cases are very similar. There is more energy cost savings in the more-hours case and the base case with technology. According to the load shapes in Figure 4 and Figure 5, these two cases either have long peak hours or have dramatic demand reduction in the peak hours. For the more-hours case, customers reduce use of electricity for a longer period of time than the base case. Thus the risk of being exposed to the high LBMP passed through form the wholesale market on hot summer days is reduced more. On the other hand, in the base case with technology, due to the higher elasticity of the customers when they are more informed and equipped with controlling technology, the resulted demand reduction in the critical peak hours is higher. Thus there is more energy cost savings in the critical hours. Interestingly, the base case with technology will cause an increase in energy cost for the customers, although it is known to be the most effective load reduction case among those four cases in the critical hours. It simply is caused by price elasticity during non-critical hours. From Figure 2, when the price ratio of dynamic rate versus flat rate is smaller than 1, the load drop goes below zero. And for the elasticity curve with enabling technology, the slope goes deep much faster than the price-only elasticity curve as the price ratio approaches zero.

It is also seen that the base case and base case with technology will incur less capacity costs for the customers in the summer. The number of critical hours is in the middle range among those cases. It shows that capacity costs do not necessarily increase with the increase of critical hour capacity price. Meanwhile, since the utilities benefit the most from the decreasing of capacity needs in the wholesale market, they should eventually pass on the economic benefits to the customers. Due to data availability, this part of analysis is beyond the scope of this study.

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