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# IMPACT OF CLIMATE CHANGE ON ELECTRICITY SYSTEMS AND MARKETS

BY

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## ABSTRACT OF THE DISSERTATION

# Impact of climate change on electricity systems and markets


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Climate change poses a serious threat to human welfare. There is now unequivocal scientific evidence that human actions are the primary cause of climate change. The principal climate forcing factor is the increasing accumulation of atmospheric carbon dioxide ($CO_2$) due to combustion of fossil fuels for transportation and electricity generation. Generation of electricity account for nearly one-third of the greenhouse (GHG) emissions globally (on a $CO_2$-equivalent basis). Any kind of economy-wide mitigation or adaptation effort to climate change must have a prominent focus on the electric power sector.

I have developed a capacity expansion model for the power sector called LP-CEM (Linear Programming based Capacity Expansion Model). LP-CEM incorporates both the long-term climate change effects and the state/regional-level macroeconomic trends. This modeling framework is demonstrated for the electric power system in the Northeast region of United States. Some of the methodological advances introduced in this research are: the use of high-resolution temperature projections in a power sector capacity expansion model; the incorporation of changes in sectoral composition of electricity demand over time; the incorporation of the effects of climate change and variability on both the demand and supply-side of power sector using parameters estimated in the literature; and an inter-model coupling link with a macroeconomic model to account for price elasticity of demand and other effects on the broader macro-economy. LP-CEM-type models can be of use to state/regional level policymakers to plan for future mitigation and adaptation measures for the electric power sector. From the simulation runs, it is shown

that scenarios with climate change effects and with high economic growth rates have resulted in higher capacity addition, optimal supply costs, wholesale/retail prices and total ratepayers' costs.

LP-CEM is also adapted to model the implications of the proposed Clean Power Plan (Section 111 (d)) rules for the U.S. Northeast region. This dissertation applies an analytical model and an optimization model to investigate the implications of co-implementing an emission cap and an RPS policy for this region. A simplified analytical model of LP-CEM is specified and the first order optimality conditions are derived. The results from this analytical model are corroborated by running LP-CEM simulations under different carbon cap and RPS policy assumptions. A combination of these policies is shown to have a long-term beneficial effect for the final ratepayers in the region. This research conceptually explores the future implications of climate change and extreme weather events on the regional electricity market framework. The significant findings from this research and future policy considerations are discussed in the conclusion chapter.

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*Where the mind is without fear and the head is held high*
*Where knowledge is free*
*Where the world has not been broken up into fragments*
*By narrow domestic walls*
*Where words come out from the depth of truth*
*Where tireless striving stretches its arms towards perfection*
*Where the clear stream of reason has not lost its way*
*Into the dreary desert sand of dead habit*
*Where the mind is led forward by thee*
*Into ever-widening thought and action*
*Into that heaven of freedom, my Father, let my country awake.*

*Rabindranath Tagore*

## Acronyms

| | |
|---|---|
| **AEO** | Annual Electric Outlook |
| **AMI** | Advanced Metering Infrastructure |
| **BRA** | Base Residual Auctions (for PJM RPM) |
| **BTU** | British Thermal Unit |
| **C** | Celsius |
| **CAIR** | Clean Air Interstate Rules |
| **CC** | Climate Change or Combined Cycle |
| **CCS** | Carbon Capture and Sequestration |
| **CCSP** | Climate Change Science Program |
| **CDD** | Cooling Degree Day |
| **CEEEP** | Center for Energy, Economics and Environmental Policy |
| **CEM** | Capacity Expansion Model |
| **CESM** | Community Earth System Model |
| **CMIP** | Coupled model inter-comparison project |
| **$CO_2$** | Carbon di-oxide |
| **CONE** | Cost of New Entry |
| **CPP** | Clean Power Plan |
| **CSP** | Concentrated Solar Power |
| **DA** | Day-Ahead (Energy market) |
| **DASR** | Day-Ahead Scheduling Reserve |
| **DMS** | Distribution Management Systems |
| **DOE** | U.S Department of Energy |
| **DV** | Dependent Variable |
| **EIA** | U.S Energy Information Administration |
| **EPA** | U.S Environment Protection Agency |
| **EGU** | Electric Generating Unit |
| **ETS** | Emissions Trading Scheme |
| **F** | Fahrenheit |
| **FERC** | Federal Energy Regulatory Commission |
| **FEMA** | Federal Emergency Management Agency |
| **FOM** | Fixed Operations and Maintenance |
| **GCAM** | Global Climate Assessment Model |
| **GCM** | Global Climate Models |
| **GCM** | General Circulation Models |
| **GCRP** | U.S Global Change Research Program |
| **GEM** | Generation Expansion Model |
| **GHG** | Greenhouse Gases |
| **GT** | Gas Turbine |
| **GtC** | Giga Ton of Carbon |
| **GW** | Gigawatt |
| **GWh** | Gigawatt Hour |
| **HDD** | Heating Degree Day |
| **HHI** | Herfindahl–Hirschman Index |
| **IAM** | Integrated Assessment Model |
| **IGCC** | Integrated Gasification Combined Cycle |
| **IPCC** | Inter-governmental Panel on Climate Change |
| **IPM** | Integrated Planning Model |
| **IPP** | Independent Power Producers |
| **ISO** | Independent System Operators |
| **IV** | Independent Variable |
| **JCPL** | Jersey Central Power and Lights |

| | |
|---|---|
| **KKT** | Karush-Kuhn-Tucker conditions |
| **LCOE** | Levelized Cost of Electricity |
| **LDC** | Load Duration Curve |
| **LIPA** | Long Island Power Authority |
| **LMP** | Locational Marginal Price |
| **LP-CEM** | Linear Programming Capacity Expansion Model |
| **LSE** | Load Serving Entities |
| **MLR** | Multiple Linear Regression |
| **MMBTU** | Million British Thermal Units |
| **MtC** | Mega Ton of Carbon |
| **MW** | Megawatt |
| **MWh** | Megawatt hour |
| **NCAR** | National Center for Atmospheric Research |
| **NetCDF** | Network Common Data Form |
| **NEMS** | National Energy Modeling System |
| **NE-ISO** | New England Independent System Operator |
| **NJ** | New Jersey |
| **NOAA** | National Oceanic and Atmospheric Administration |
| **NOx** | Oxides of nitrogen |
| **NPV** | Net Present Value |
| **NSF** | National Science Foundation |
| **NTSD** | Non-temperature sensitive demand |
| **NYC** | New York City |
| **NYISO** | New York Independent System Operator |
| **PJM** | Pennsylvania-New Jersey-Maryland Interconnection |
| **PSE&G** | Public Service Electricity and Gas |
| **PUC** | State Public Utilities Commission |
| **PUHCA** | Public Utilities Holding Companies Act |
| **PURPA** | Public Utilities Regulatory Policies Act |
| **PV** | Photovoltaic |
| **RCPs** | Representative Concentration Pathways |
| **RCM** | Regional Climate Model |
| **R&D** | Research and Development |
| **R/ECON** | Rutgers Economic Advisory Services |
| **ReEDS** | Regional Energy Deployment System Model |
| **REC** | Renewable Energy Credit |
| **RGGI** | Regional Greenhouse Gas Initiative |
| **RIA** | Regulatory Impact Analysis |
| **RT** | Real time (Energy market) |
| **RTO** | Regional Transmission Organization |
| **SCADA** | Supervisory Control and Data Acquisition |
| **$SO_2$** | Sulfur dioxide |
| **TPS** | Three Pivotal Supplier Test |
| **TSD** | Temperature sensitive demand |
| **TWh** | Terawatt Hour |
| **VOM** | Variable Operations and Maintenance |
| **WRF** | Weather Response Function |

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# Chapter 1

# Introduction

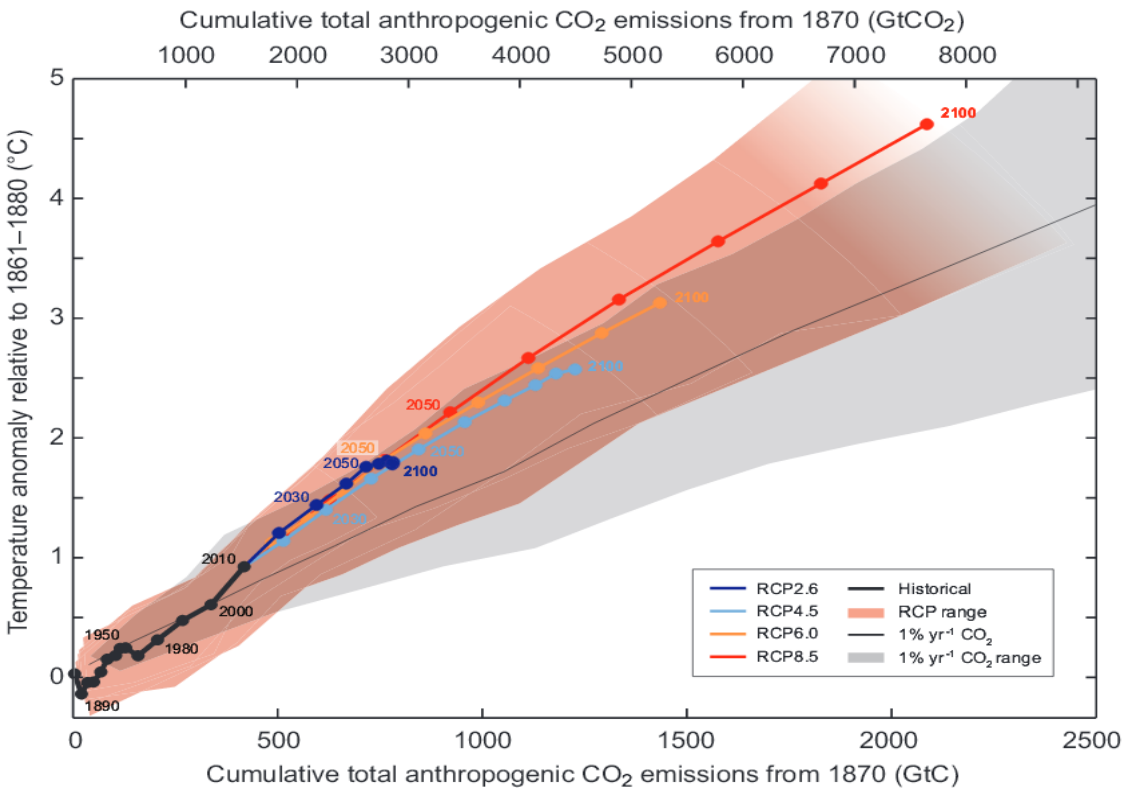
## 1.1 Motivation

There is now unequivocal scientific evidence that human actions are the primary cause of climate change (National Research Council, 2010; IPCC, 2013; Hansen et al., 2013; Melillo et al., 2014). The principal climate forcing factor is the increasing accumulation of atmospheric carbon dioxide ($CO_2$) due to combustion of fossil fuels for transportation and electricity generation. The current consensus among global policymakers is to cut down the global emissions so as to hold the global mean temperature increase to 2 degrees Celsius or less (UNFCC, 2009). Based on the output from leading global climate-carbon cycle models, this global warming target roughly translates to 1000 GtC of cumulative atmospheric emissions (see Figure 1.1 from IPCC, 2013). Figure 1.1 is illustrative of the challenges confronting our society in the coming years. Based on positive feedback effects (like vegetation feedback and ice-albedo effects) and non-$CO_2$ forcings (like methane emissions), this upper bound on $CO_2$ accumulation is further constrained to about 790 GtC (IPCC, 2013). At present, the global cumulative emissions stand at 515 GtC (as of 2011). For the next thirty years, the global emissions are expected to range between 10-18 GtC for each year (Levin, 2013; Hansen et al., 2013). Land and ocean sinks have the potential to remove nearly 5.5± 1.3 GtC a year[1] (Global Carbon Project, 2014). At the current emissions level, it would imply a deadline of *30 years or less* before the temperature target of 2 degree Celsius is breached. Stabilizing the global carbon budget calls for substantial reductions in GHG emissions over the next few decades and near zero emissions by the end of the century. Reductions of this magnitude can only be achieved through a

[1] These are global average estimates for the years 2004-13. The effectiveness of carbon removal from these natural sinks could decline in the coming years.

concerted global effort and mitigation efforts targeting all sectors of the economy. The electric power and transportation sectors have a prominent role in this long-term stabilization effort.

**Figure 1.1 Cumulative $CO_2$ emissions and global mean temperature increase relative to a historic period**




Reproduced from IPCC: Working Group I: Physical Science Basis- Summary for Policymakers (2013) (p.28)

The production of electricity and heat from fossil fuel sources account for nearly 25% of the global GHG emissions in 2010 (IPCC, 2013: p.8). In addition, the indirect emissions from the energy sector account for an additional 9.6% of the GHG emissions (ibid.). Any kind of economy-wide mitigation or adaptation response to climate change must have a central focus on the electric power sector. In the United States, the electric power sector account for 32% of the total annual $CO_2$-equivalent GHG emissions (EPA, 2014). Several states in the U.S have adopted stringent targets for "deep reductions" in GHG emissions (Williams et al., 2012). States like New Jersey and California have mandated an ambitious GHG emissions reduction

target of 80% by 2050 (compared to 1990 levels for California and 2006 levels for New Jersey)[2]. But there have been very few realistic modeling studies in the literature that have captured the energy and economic transformation required to achieve such drastic emissions reduction[3]. The electric power sector is projected to contribute substantially to the proposed emissions reductions (see Pacala and Socolow, 2004 for potential emission reduction "wedges" related to the power sector). The emissions reduction strategies and other policy interventions (like renewables standards, energy efficiency standards and R&D support for renewables) are expected to result in a *carbon constrained* future for the power sector.

At the same time, the electric power sector is critical to the U.S economy. For the year 2012, the utilities industry (which includes electric, gas and water distributions) contributed a "value addition" of nearly $275 billion to the overall national GDP[4]. This metric is an underestimation of the importance of the electric power sector to the overall macro-economy. Electricity is the primary energy source for different sectors of the economy like agriculture, mining, manufacturing, healthcare, information technology and governmental services. Despite end-use energy efficiency improvements, electricity demand in the U.S is expected to grow at 0.8% a year from 3,686 TWh in 2012 to 4,632 TWh in 2040 (EIA, 2014). This increase is attributable to economic growth, demographic changes and climate effects. With the projected electrification of the transportation sector, the economic and environmental importance of the power sector is said to increase in the coming years (Morgan et al., 2005; Williams et al., 2012).

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[2]For NJ see: http://www.nj.gov/globalwarming/home/gwra_report.html & For CA see: http://www.arb.ca.gov/cc/ab32/ab32.htm

[3] One exception is Williams et al. (2012) who comprehensively model the emissions reduction scenarios in California and its impact on the power sector.

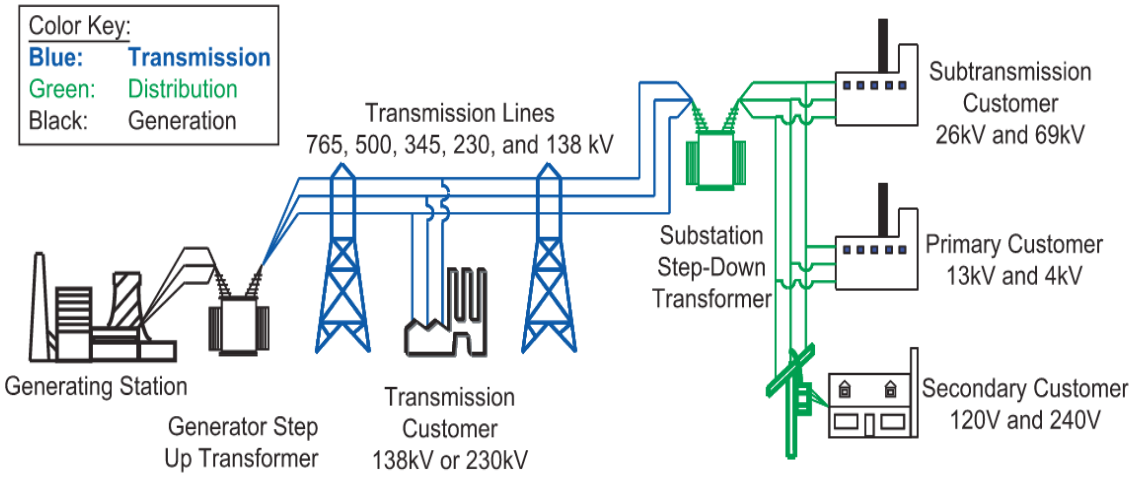
[4] Value addition is defined as "... the contribution of each industry's labor and capital to its gross output and to the overall gross domestic product (GDP) of the United States. Value added is equal to an industry's gross output (sales or receipts and other operating income, commodity taxes, and inventory change) minus its intermediate inputs (consumption of goods and services purchased from other industries or imported)". See: Bureau of Economic Analysis- Gross Domestic Product by industry data. http://www.bea.gov/industry/gdpbyind_data.htm

The electricity market has been transformed profoundly in the last two decades. Many states, especially in the Northeast, have migrated from a franchisee-based monopolistic system to a market-competition based system of electricity markets. For the first seven decades since the commercialization of electric power, the real average price of electricity has declined steadily. However since the 1970s, the real average prices have exhibited an increasing trend (EEI, 2006 and Hogan, 2010). Reconciling the growing demand for a cost-effective and reliable source of electric power with the implementation of "deep reductions" in GHG emissions is a challenging proposition for the industry and its policymakers.

## 1.2 Overview of the electric power sector

Electricity is an integral part of the global energy system. Electrical energy is a *sine qua non* for overall societal welfare and economic growth. Since the introduction of electrical power as a commercial energy source in the 1890s, the core technical aspect of the electric power sector has changed little. The overall set-up of a typical electric power system is depicted in Figure 1.2. The electric power system is comprised of centralized and distributed power plants that generate electricity, transmission lines that carry high-voltage electric power over long distances, sub-stations that step down the electric voltage to distribution levels and distribution lines that serve the end consumers. Power plants are often located near an energy source, like a coal mine or a dam, to minimize the fuel transportation costs. Often times, these power plants are located away from heavily populated load-centers. Hence, there is a need to economically transport the electricity generated. This is done by transmitting the generated power at a high voltage (stepping-up at the power plant and stepping-down at the sub-station using a transformer at both ends). From the sub-stations, the power is then distributed to end consumers by means of distribution lines. Presently, the U.S has three main grid networks the Eastern Interconnection, the Western Interconnection and the Electric Reliability Council of Texas (ERCOT). The New York-New Jersey (NY-NJ) region is part of the Eastern Interconnection network.

**Figure 1.2: Key components of an electric power system**




Source: US-Canada Power System Outage Taskforce Report- August 14th Blackout: Causes and Recommendations (p.5)

A range of public and private institutions manages and regulates this infrastructure. As of 2012, there are around 2,200 traditional utilities in the United States handling the entire cycle, from power generation to power delivery, for over 145 million customers of various customer classes[5]. These traditional utilities can be investor-owned, publicly-owned (usually at a municipal level), consumer-owned co-operatives or Federally-owned. There are also about 1,700 power producers of the following types: "qualifying facilities" (renewable energy and combined-heat-and-power (CHP) units under the Public Utility Regulatory Policies Act of 1978 (PURPA)); independent power producers (companies that generate and sell electricity at wholesale market-rate to traditional utilities); and other stand-alone CHP units. The traditional utilities are subject to Federal, state and local laws on aspects ranging from corporate practices to local environmental impacts. Except for Texas ERCOT, which is not operationally synchronized with the rest of the country, interstate sale of electricity on the wholesale market between utilities is regulated by the Federal Energy Regulatory Commission (FERC). FERC also regulates interstate transmission, issues regulations for grid reliability and oversees market and operational practices of system operators. In

[5] US Energy Information Administration- Form 861 (2012)- http://www.eia.gov/electricity/data/eia861/

addition to FERC, the grid reliability at a regional (generation and transmission) level is enforced by Independent System Operators (ISOs)/Regional Transmission Organizations (RTOs). These ISOs/RTOs are regulated, non-profit entities. New Jersey is governed by an ISO called the PJM Interconnection[6], which handles grid operations and administers the competitive wholesale market in all or parts of thirteen states and District of Columbia. The New York ISO (NYISO) administers the wholesale markets and operates the grid for the state of New York alone (including Long Island). At a state-level, the electric utilities are also subject to state Public Utilities Commissions (PUCs) which mostly regulates retail operations and ratepayers' interest. State and federal environmental regulators also play a critical role in regulating the environmental impacts of the electric power sector. In sum, the electric power sector in the U.S operates under a complex and multijurisdictional regulatory landscape.

Until the early 1990s, the power sector in the U.S and in most other countries operated on a "rate-base" paradigm of cost regulation. For decades under these arrangements, the real average price of electricity exhibited a steady decline (EEI, 2006). Under this scenario of declining average costs and high demand growth, the electric power industry's main concern was meeting system demand by investing in new capacity. However, in the mid-1970s, average retail prices began trending upward, mostly due to decreasing returns to scale on the generation side, moderation of demand growth, and higher fuel prices. Also, the utilities under a regulatory regime had the perverse incentive of expanding their "rate-base" (by means of excess capital investments) on which they were entitled to earn a rate of return from ratepayers. This tendency led some electric utilities to adopt excessively capital-intensive technology and consequently pass on the higher retail prices to final ratepayers[7]. The passage of PURPA in 1978 was a catalyst for independent investors to enter the electric power sector. This legislation exerted pressure on

[6] The abbreviation "PJM" reflects the original three states in its formation: Pennsylvania, New Jersey, and Maryland.

[7] This is called gold-plating or Averch-Johnson (AJ) effect in regulatory parlance. See Averch and Johnson (1962) and Kahn (1988) for the theory and implications of AJ effect on regulated utilities.

the generators to improve production efficiencies. These underlying market changes, accompanied by an overall macroeconomic policy shift towards liberalization, led to the restructuring of electricity markets in the U.S starting in the late 1980s (Joskow and Schamalensee, 1983; Kahn, 1988). It was thought that a restructured market could improve the market efficiencies on the production and pricing aspects of the power sector. The competitive framework hinges on the principle of equating the price of the good to the marginal cost of meeting the demand. For the electricity market, this would translate as the marginal variable cost of the last generator unit that needs to be dispatched to meet the system demand (Hogan, 1998). As of 2010, fifteen states, including New Jersey and New York, have adopted a restructured electricity market with different degrees of competition in retail and wholesale markets[8]. Ten out of the fifteen states that have implemented market restructuring are based in the Northeast region. This could be a consequence of the higher than average retail prices in the region. Seven states, including California, have tried to implement restructuring in the past but have now fully or partially suspended such efforts. Remaining states continue to operate under a traditional "rate-base" paradigm.

## 1.3 Project background

In March 2011, a consortium of researchers from Rutgers University and National Center for Atmospheric Research (NCAR) were awarded a National Science Foundation (NSF) grant to study the effects of climate change on the urbanized coastal environment in the Northeast region of the U.S[9]. The thrust of the project is on "coupling" the physical climate models to key human systems models. The electric power system is one of the three humans systems modeled under this effort, the other two being a state macroeconomic

[8] US EIA- http://www.eia.gov/electricity/policies/restructuring/restructure_elect.html

[9] NSF OCE Award: 1049088. For an abstract of the project search using the following link: http://www.nsf.gov/awardsearch/

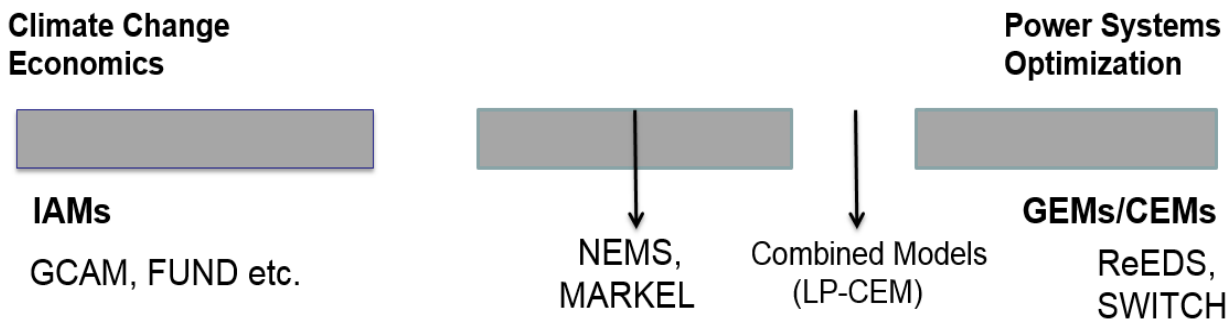
model (R/ECON[10]) and a coastal land-use model. The research motivation for modeling the electric power sector is threefold:

- The electric power sector is the single largest point source of carbon dioxide and other pollutants like oxides of nitrogen, sulfur dioxide, mercury and other particulate pollution (Morgan et al., 2005; EPA, 2014). Any kind of economy-wide mitigation effort ought to focus on the electric power sector.
- A transition to a low-carbon economy requires a rapid de-carbonization of the existing fossil fuel-based generation portfolio (Williams et al., 2012; Fripp et al., 2012). Currently, the power industry has various options to implement such a transition. The technology-based options include deployment of more renewables, improvement of heat rates for new and existing plants, a switch to less polluting fuels like natural gas and deployment of advanced carbon capture and sequestration (CCS) technologies. Demand/supply-side operational options include end-use energy efficiency improvements, demand response programs, dynamic pricing mechanism and other smart grid technologies. In addition to reducing $CO_2$ emissions, many of these options also help to reduce other power sector pollutants like NOx, $SO_2$, mercury and particulate matter.
- The electric power sector is saddled with assets that have a long economic life. The economic life of a conventional fossil fuel or nuclear power plant is around 40-60 years (Morgan et al., 2005; Davis et al., 2010). Stabilizing global atmospheric carbon levels by mid-century calls for massive deployment of low- to zero-carbon technologies *starting today*. In order to ensure that the electric power sector is geared up to meet the future challenges of climate change and other market transformations, there is a need to accurately project the multi-decadal trends in systems and markets through models and simulations.

[10] R/ECON™ is a quarterly structural econometric time-series model of New Jersey. It consists of over 250 equations that estimate, among other things, state GDP, personal income, inflation, energy prices, demand, unemployment, local and state tax revenues etc. - http://policy.rutgers.edu/cupr/recon/about.php

As an initial step in the modeling process, a review of existing power sector models that incorporate climate effects was executed (see Chapter 2 for a more detailed literature review). Figure 1.3 represents the broad spectrum of existing literature on such models. On the climate change economics- end of the spectrum, Integrated Assessment Models (IAMs) simulate the complex interaction between the environment and socio-economic systems (see Kelly and Kolstad (1998) and Peterson (2004) for a literature overview on IAMs). These models integrate aspects like land use, energy flows, carbon cycle, macroeconomic changes and population/technological changes over time. There are equilibrium models focused on the broader energy sector and the inter-connecting energy conversion pathways. A good example is EIA's National Energy Modeling System (NEMS) which has dedicated modules for supply, demand, conversion and economy modules. On the power systems-end of the spectrum, there are generation expansion models (GEMs), unit commitment and dispatch models, optimal power flow models, production cost models and demand/price forecasting models. For long-term modeling, planners rely on generation expansion and production cost models. GEM is better suited to model the changes to the supply and demand-side of the power sector at a broad temporal and geographic resolution. GEM involves selecting the type of generating technology to be added to an existing power grid and answering the question of when and where these new power plants must be constructed to meet the demand in the given planning horizon. The proposed Linear Programming- Capacity Expansion Model (LP-CEM) framework is a detailed, regional version of a GEM with coupling links to climate projections from a climate model and economic projections from a state macroeconomic model (R/ECON).

**Figure 1.3: Positioning the proposed model in the broad spectrum of existing literature**




Several research contributions are developed in the course of this dissertation. First, this research has adapted a GEM/CEM modeling framework to study the effects of climate change and macroeconomic trends on a regional/state-level basis. The LP-CEM model is executed under plausible climate and economic growth scenarios for New Jersey and the wider Northeast region of the U.S. Only a few studies in the literature have analyzed the climate change impacts on the power sector at a *region or state-level* (like Vine (2008); Williams et al. (2012); Fripp et al. (2012)) Such models can help state/regional-level policymakers, related to the electric power sector, plan for future mitigation and adaptation measures and to assess the impacts of various policy interventions on energy investments and macroeconomic outcomes. Second, this research effort has established a coupling framework between a macroeconomic and a power sector model. The coupling framework provides a feedback loop to analyze the impact of climate change and macroeconomic trends on the power sector and in turn analyze the effect of electricity price changes on the overall state macro-economy (through a measure of state GDP) and energy demand. This "coupling loop" is continued until a convergence is achieved in key economy-energy sector parameters. Third, the LP-CEM modeling framework is used to analyze the interaction effect of multiple policy instruments on capacity expansion pathways and retail/wholesale prices. In this research, the LP-CEM is used to analyze the societal cost implications of implementing an emissions cap policy with a renewable portfolio standards (RPS) for the Northeast region. The use of a GEM framework to explain the interaction effect of mitigating policy instruments has not been explored in the literature before (see del

Rio, 2007). In addition to these contributions, this dissertation also addresses the possible impacts of climate change on the design features of wholesale electricity markets in the Northeast. The key innovative features of the LP-CEM modeling framework are tabulated in Table 1.1. The key research questions addressed in this dissertation research are tabulated in Table 1.2.

**Table 1.1: Innovative features of the modeling framework**

| |
|---|
| • Use of station-level temperature projections data from a global climate model (NCAR's CESM)<br>• Interface with a state/regional macroeconomic model (R/ECON)<br>• A two-way coupling with a macroeconomic model enabling a feedback loop<br>• Use of LP-CEM to quantify and analyze the societal costs of multiple policy instruments<br>• Use of LP-CEM to project the possible implications for the wholesale electricity market design |

**Table 1.2: Key research questions addressed by this dissertation**

| |
|---|
| What are the key impacts of climate change on electricity systems and markets? What is the current state of energy policy literature on such impacts?<br><br>What are the challenges and implications in incorporating macroeconomic and climate change effects in a generation/capacity expansion model (GEM/CEM) of the power sector?<br><br>What are the major long-term changes to the nature of electricity supply and demand in New Jersey (and in the wider Northeast region) under plausible climate and socio-economic scenarios?<br><br>What are the key quantitative policy insights from LP-CEM model runs for New Jersey and the wider Northeast region? (like nature of capacity expansions, electricity prices and ratepayers' cost)<br><br>How does the interaction of multiple policy instruments, targets, scope and tiers of policymaking affect the overall cost optimization of the electric power sector? How does the interaction of the proposed emissions cap and RPS policy play out for the Northeast region?<br><br>What are the likely planning and policy implications of climate change on future wholesale market design? What market design and regulatory changes, if any, are needed to respond to climate change?<br><br>What are the planning and policy implications for meeting the future challenges of climate change and extreme events? |

## 1.4 Chapter Description

This dissertation is organized as follows:

- Chapter 2 is a literature review of power sector assessment models that analyze the impact of climate change on electricity systems and markets. The chapter critically analyzes the architecture of existing assessment models for the power sector, the key demand and supply-side forecasts/projections from such models, and the gaps and advances in the state of knowledge on climate change impacts. This chapter has been published earlier as a journal article with my dissertation advisor as the co-author (see Chandramowli and Felder, 2014a).
- Chapter 3 explores recent advancements in climate data projections and the attendant challenges and opportunities in incorporating these climate projections in a power sector model. This chapter also explores the nature of uncertainty in the context of LP-CEM framework. An adapted version of this chapter has been published earlier as a journal article with my dissertation advisor as the co-author (see Chandramowli and Felder, 2014b).
- Chapter 4 introduces LP-CEM (Linear Programming Capacity Expansion Model), a power systems expansion model that was developed during the course of this dissertation research. LP-CEM incorporates both the long-term climate change effects and the state/regional level macroeconomic trends. This modeling framework is demonstrated for the New Jersey region. A two-way coupling is established between LP-CEM and R/ECON to analyze the feedback effects between changes in electricity prices and broader state-wide macroeconomic trends.
- Chapter 5 analyzes the policy interaction effect of an RPS and an emissions cap instrument for the Northeast region of the U.S. This chapter uses a detailed, regional version of the LP-CEM to analyze the marginal abatement costs, supply cost trends and price implications under plausible policy mix scenarios.
- Chapter 6 looks at some of the other impacts of climate change and variability that are not captured in the LP-CEM framework. It covers two important aspects of power sector impact assessment: the impacts of extreme events on the power sector and the implications of climate

change and variability on electricity market structure. An overview of the electric power sector restructuring effort in the U.S is also presented in this chapter for the reader's benefit. This chapter analyzes the possible future implications for PJM's institutional features and market structure.

- Chapter 7 summarizes the key findings from this dissertation research, formulates a set of broad policy recommendations for the electric power sector to meet the future climate change challenges, and concludes with a brief account of current research limitations and pointers for future improvements.

# Chapter 2

## Impact of climate change on the electric power sector- A literature review [11]

Climate change and variability poses a serious challenge for electricity production and use. Understanding climate change and its impacts on electric power systems is crucial for planning and implementing economy-wide mitigation and adaptation policies in the future. This review highlights the research areas where the knowledge frontier has advanced significantly, such as: temperature-sensitive demand estimation, plant-level effects of cooling water/ambient air temperature increase, supply vulnerabilities due to decreased water availability for power generation, and localized impact of climate variations on wind resources. The research areas where the impacts remain unclear include: system-wide impact on renewable and thermal power generation, economic modeling of extreme events, vulnerabilities of transmission and coastal energy infrastructure to extreme events, long-term combined modeling at a state or regional level, and the effects of *climate, impact* and *policy* uncertainty on modeling outcomes. The outcome of this research review is intended to inform the design of future electricity markets and system models.

### 2.1 Introduction

Climate change poses a serious challenge for electricity production and use (IPCC, 2014; Statham et al., 2014). The electric power sector is both a contributor to climate change and a sector that is vulnerable to disruptions due to climate change effects. Some of the key environmental effects of climate change are: rise in global surface temperature, changes to hydrological cycles, ocean acidification, rise in mean sea levels and higher incidences of extreme weather events (like storm surges, heavy precipitation and heat waves) (Melillo et al., 2014). The disruption to the generation and supply of electricity could be considerable due to these environmental changes. The global energy demand is expected to increase in the coming years, thereby causing the GHG emissions from the power sector to increase as well (Statham et al., 2014). Understanding climate change and its impacts on electric power systems is crucial for planning and implementing economy-wide mitigation and adaptation policies in the future.

[11] This chapter was previously published as a journal article. See: Chandramowli and Felder (2014a)

The current increase in global atmospheric $CO_2$ is mainly due to combustion of fossil fuels for transportation and electricity generation (IPCC, 2013). In the U.S, the electric power sector is the single largest source of GHG emissions, accounting for nearly 32% of the total (US EPA, 2014).Due to anthropogenic emissions of $CO_2$ and other greenhouse gases (GHG), the heat trapping ability of the atmosphere is amplified (National Research Council, 2010). This causes an increase in global surface temperature. In addition, the electric power sector is also the single largest source of sulfur dioxide ($SO_2$), oxides of nitrogen (NOx), mercury and other particulate emissions (Morgan et al., 2005). Stabilization of GHG emissions at a level compatible with the global temperature increase target of 2 degree Celsius or less entails a fundamental transformation of the electric power sector (also see discussions in Section 1.1). This transformation is likely to involve rapid de-carbonization of generation portfolio; reductions in emissions associated with fuel extraction and conversion; improvement of power plant efficiencies in generation; switch to low-carbon fuels; and deployment of renewables, nuclear generation and carbon capture and sequestration(CCS) technologies. Capital stock in the form of generation, transmission and distribution assets must also adapt to meet these challenges in the coming years. To complicate matters, the electricity sector is burdened with assets that have a long-lasting economic life. To ensure that the electricity sector is best suited to meet the challenges of climate change in the coming decades, there is a crucial need to accurately project the multi-decadal trends in electricity markets and systems.

## 2.2 Nature of the modeling problem

Broad-based research on the impacts of climate change on electric power sector has been “surprisingly scant” in the literature (Mideksa and Kallbekken, 2010). We define power sector assessment models based on three criteria. They include models that: (1) focus on the electric power sector primarily, (2) incorporate realistic climate projections from a climate model run, and (3) explore the impact pathway of changing climate variables on power sector parameters. Only a few studies have analyzed climate change impacts on the power sector at a *region or state-level* (like Williams et al. (2012); Fripp et al. (2012); Vine

(2008)). Also, we are not aware of any comprehensive attempt to explain the impact of climate change on the features of the electricity market[12]. In the absence of an assessment of power sector impact literature, formulating a policy response to climate change is a challenging proposition for policymakers. The one detailed assessment-type study on power sector impacts that we could find is that of Mideksa and Kallbekken (2010) (at the time of writing). But this study focuses primarily on model outputs and projections. To the best of our knowledge, there has been no prior attempt to review the *architecture* or the *methodology* of such models. Hence a review of the model architecture and key forecasts, as proposed in this chapter, could help to inform the research on power sector impact modeling and also be of use to policymakers connected to the power sector.

The power sector has traditionally relied on models and simulation runs for operational and planning problems like generation and transmission expansion, demand forecasting, economic dispatch scheduling, and optimal power flow. Recently, power sector assessment models have emerged in the literature to model the potential impacts of climate change. This chapter is a review of such models in the literature. The nature of the problem from the perspective of a potential model developer can be analyzed under *three* distinct dimensions (see Figure 2.1). The three dimension are the *scale* of the problem; the *scope* of the problem and the *uncertainty* in the problem. First, a graphical representation of the *spatial* and *temporal scale* of planning activities in electricity markets is presented in Figure 2.2 (partly adapted from Coughlin and Goldman, 2008). The operational and planning problems (such as nodal pricing, demand forecasting, and resource planning) are plotted based on the time and spatial scale at which they are modeled. The X-axis represents the increasing geographic/spatial scale and the Y-axis represents the increasing time scale. The X-axis ranges from a node in the electric power grid to a regional/national grid

[12] Electricity markets refers to the market system of effecting the sale of electricity commodity (i.e. usually in MWh) between generators and utilities by balancing the supply offers and demand bids, subject to technical constraints. Electricity markets are a key feature of a restructured electric power sector.

network. The Y-axis ranges from a sub-hourly to a multi-decadal timeframe basis. Power sector assessment modeling is situated at the top-right corner of Figure 2.2. To account for these *spatial* and *temporal* scale effects of climate change, the LP-CEM framework considers a multi-decadal and a regional level modeling scale.

**Figure 2.1: Schematic representation of the dimensions of the modeling problem at hand**

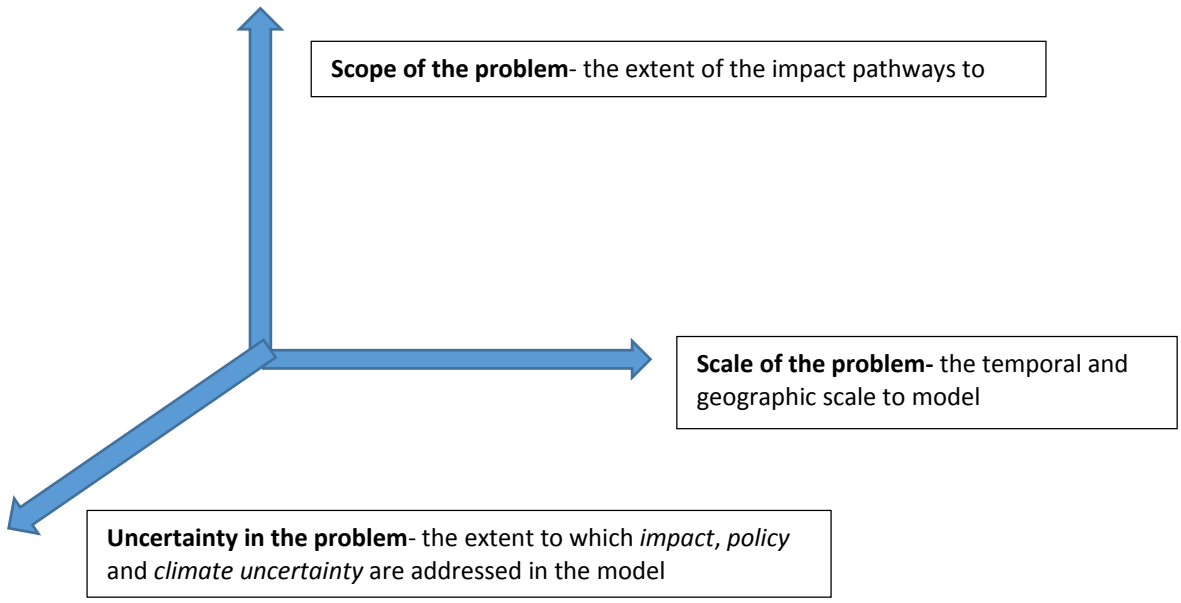
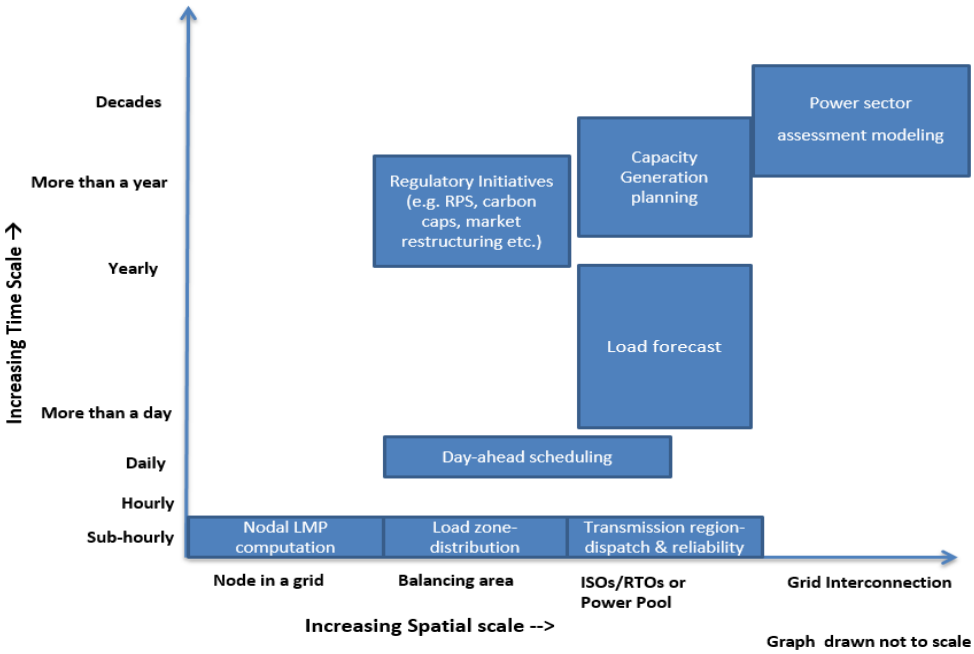



**Figure 2.2: Temporal and spatial scale of planning problems in electricity systems and markets**



Second, consider the *scope* of the planning problem and its implications. Some of the documented implications of climate change on electricity systems and markets are summarized in Table 2.1 and 2.2. A potential model developer, interested in analyzing the climate change effects on the power sector, must at the very least incorporate *some* of these implications in the model. The empirical relationship for many of these implications are not fully explored in the literature. Power sector assessment models can help to quantify these impact pathways. The proposed R/ECON-LP-CEM framework integrates a power sector capacity expansion model (CEM), a regional macroeconomic model and temperatures projections from a climate model run. This framework also offers the flexibility to analyze the impact of regulatory initiatives like RPS and emissions cap on the electric power sector. In the U.S. context, such models can help policymakers, like the state public utilities commission (PUCs), electric utility companies, independent system operators (ISOs)/regional transmission operators (RTOs) and the Federal & state governments, to evaluate competing policies and to chart out a long-term plan for the power sector.

**Table 2.1: Implications of climate change on demand-side attributes of the electric power sector**

| Demand System Component | Climate Change Effect | Implications |
|---|---|---|
| Cooling demand | Elevated ambient temperatures, extended and more intense summers | Increase peak system demand in summers, increase in overall electricity demand, and increase in air conditioner usage |
| Non-temperature sensitive demand (NTSD) | Extended dry seasons and increase in cooling water temperature | Affects CHP unit operation and frequent demand response initiations to avoid system blackouts |
| Peak demand | Intense summers, warmer and shorter winters | Annual double peak demand pattern (with a high summer peak and a comparatively lower winter peak) |
| Load Duration curves (LDCs) | Systematic changes in economy-wide demand patterns and extreme weather events | Higher peak system demand and higher annual load variations. Increase in chances of exceeding market price caps, changes to capacity market design |

Source: Coughlin and Goldman 2008; Mideksa and Kallbekken, 2010; US-CCSP, 2008.

**Table 2.2: Implications of climate change on the supply-side attributes of the electric power sector**

| Supply System Component | Climate Change Effect | Implications |
|---|---|---|
| Hydropower generation | Changes to long-term precipitation trends, inter-seasonal variations in river flow | Affects hydropower production, affects pumped storage operations and increase in risk of flooding |
| Thermal power generation | Increase in ambient air temperature | Decrease in efficiencies of power generating equipment like gas and steam turbines |
| | Increase in cooling water temperature | Decrease in thermal efficiencies of power equipment, affects marine life at plant discharge and possible generation curtailment |
| | Increase in frequency of extreme heat events and reduced water availability | Generation curtailment, expensive adaptation changes for cooling systems, affects plant siting decisions |
| Transmission and distribution infrastructure | Higher ambient temperature | Reduced transmission/ distribution line carrying capacity (due to thermal limits) and increase in risk of system blackout due to power line sagging |
| | Frequent coastal /inland flooding, increase in mean sea level and other extreme events | Increase in risk of physical damage to coastal energy infrastructure and affects future plant siting decisions |
| Solar power generation | Increase in ambient air temperature; changes to insolation (or cloud cover) | Decrease in energy output from solar panels and CSP systems; decrease in efficiency due to increased ambient air temperature |
| Wind energy generation | Changes in diurnal and seasonal wind pattern | Increase in generation variability; damages to wind turbines due to extreme weather events; intermittency in generation output; grid reliability issues |

Source: Coughlin and Goldman, 2008; Mideksa and Kallbekken, 2010; US-CCSP, 2008; DOE, 2013.

Third, a potential model developer should be aware of the nature of *uncertainty* in the modeling problem.

For simple elucidation purposes, we have classified the uncertainty in the modeling problem under three

categories: *climate, impact and policy types*. The climate uncertainty refers to the uncertainty in projecting the future weather/climate. The impact uncertainty broadly refers to the unknown nature of the impact pathways of climate variables to power sector parameters. The policy uncertainty refers to the possible future policy and socio-economic settings. The nature of uncertainty in the context of LP-CEM modeling framework is explored in detail in Section 3.3 of the next chapter. (For a more in-depth understanding of the nature of uncertainty in climate change assessment modeling, refer Schneider and Duriseti (2002); Nordhaus (2008); Hawkins and Sutton (2009)).

Mideksa and Kallbekken (2010) is one of the earliest attempts in the literature to review the impacts of climate change on electricity systems. They assessed the research literature on this topic and have identified four significant knowledge gaps. These gaps are: regional demand-side impacts in Asia, Africa, Caribbean and Latin America; the effect of extreme weather events on electricity systems; changes to the adoption rate of air conditioners; and sensitivity of thermal power supply to changes in air and water temperature. Whereas Mideksa and Kallbekken (2010) focus on the results of assessment models that dealt with climate change impacts on electricity systems, this review synthesizes and compares the key framework and parameters of the various electricity models themselves. Also, the focus of this dissertation is limited to the impact of climate change on *electricity* systems and markets, and *not* on the broader energy system. Power sector assessment models can be broadly organized into *three* categories: models that focus on demand-side effects, on supply-side effects, and combined models that deal with both demand- and supply-side effects.

## 2.3 Models focusing on demand-side impacts

Built environments like households and commercial establishments use electricity for comfort heating/cooling, lighting, refrigeration, and operating equipment. Residential and commercial sectors

account for more than two-thirds of the total electricity demand in the world[13]. The effect of temperature increase on space heating and cooling is well explored in the literature. At present, virtually all of the cooling demand is met by electricity (by means of an air conditioner), while the heating demand is met by a combination of electric power, natural gas and fuel oils. Linder and Inglis (1989) is one of the earliest comprehensive studies of climate change impacts on the electricity sector in the U.S. The study projects a 14-23% additional capacity investment relative to a non-climate change scenario for the years 2010 to 2055. Except for Jaglom et al. (2014), none of the reviewed studies account for sectoral composition of system demand (i.e. differentiate system demand by residential, commercial and industrial sectors).

Although there is a rich literature on short- to long-term electricity demand forecasting (see Weron, 2006; Suganthi and Samuel, 2012), this reviews focuses only on research studies that have explicitly modeled climate change effects on a long-term basis. Based on the studies reviewed, the demand-side impacts of climate change have been modeled under three distinct approaches: multiple linear regression (MLR), bottom-up energy accounting and fuzzy regression. Out of the three approaches, nearly 90% of the reviewed papers employ a MLR model approach. This approach is analyzed in greater detail in the following paragraph. A brief definition of the three remaining methodologies is presented here for the reader's benefit. A bottom-up energy accounting involves computing the effects of warming temperature on building energy consumption using building energy simulation models. The energy changes are then projected at an economy-level using building stock and overall energy consumption pattern. A fuzzy regression is a modified version of the regression model with capabilities to handle the fuzzy and point estimates of regression coefficients (see Shakouri and Nadimi, 2009; and Zaman and Shakouri, 2010).

Most studies use a linear regression equation to model the impact of temperature increases on electricity and gas demand. Either energy, gas or electricity demand is the typical dependent variable in these

[13] International Energy Agency- Key World Energy Statistics 2012 (p.37)- http://www.iea.org/publications/freepublications/publication/kwes.pdf

models. These MLR models use a set of weather and economic variables as the independent variables to project the electricity demand in the future. Many of the reviewed papers use simple increase in average temperatures as the climate change scenario. Only four of the reviewed papers use temperature projections from global climate models run to model the transient effects of temperature increase as well (Rosenthal and Gruenspecht, 1995; Hadley et al., 2004; Scott et al., 2005 and Huang, 2006). Using the MLR approach, there are demand-side impact studies at a *national scale* (see Rosenthal et al., 1995; Scott et al., 2005, Hadley et al, 2005, Mansur et al., 2005 for the U.S.; Parkpoom et al. for Thailand and Howden and Crimp, 2001 for Australia) and a limited number of studies at a *regional scale* (see Amato et al., 2005 for Massachusetts, Ruth and Lin, 2006 for Maryland, Miller et al., 2007 for California). Most of the demand-side studies focus on advanced industrial economies. A few studies focus on developing economies like Parkpoom et al. (n.d.) on Thailand and Mirasgedis et al., 2007 on Greece.

The consistent implication from these studies is that the overall *primary energy* demand is expected to *increase* in the future due to growth in population, economic output and climate effects. It is generally predicted that an increase in mean surface temperature is likely to reduce the heating energy demand for colder regions in Europe and North America. However the net effect of the surface temperature increase for individual fuel demand (like heating oil or natural gas) or the overall effect at a national level is not clear in the literature. Also, regional projections differ based on scenario, climate projections and socio-economic assumptions. Increasing adoption of air-conditioners is expected to contribute to an increase in electricity demand for cooling. Very few papers have actually modeled the effect of widespread air-conditioner adoption on the overall system demand (see Sailor and Pavlova (2003) and Issac and van Vuuren, (2009) for ways to model the effect of increasing air-conditioner adoption). Thus, the combination of warming weather and increasing adoption of air conditioners is expected to substantially increase the electricity demand in the coming decades. The effect of changing building stock and energy efficiency measures is documented only in two of the reviewed studies (in Scott et al., 2005 and Huang, 2006). Miller

et al. (2008) also looks at the impact of higher summer temperature on peak system demand. The study estimates that the peak system demand in California is expected to increase linearly for temperatures beyond 82°F at the rate of 700 MW per 1°F. Other studies like Pyror and Bartheline (2010) and Sailor and Pavlova (2003) report a non-linear increase in peak system demand at elevated temperatures. In general, extreme heat events in the future are expected to result in higher system peak demand.

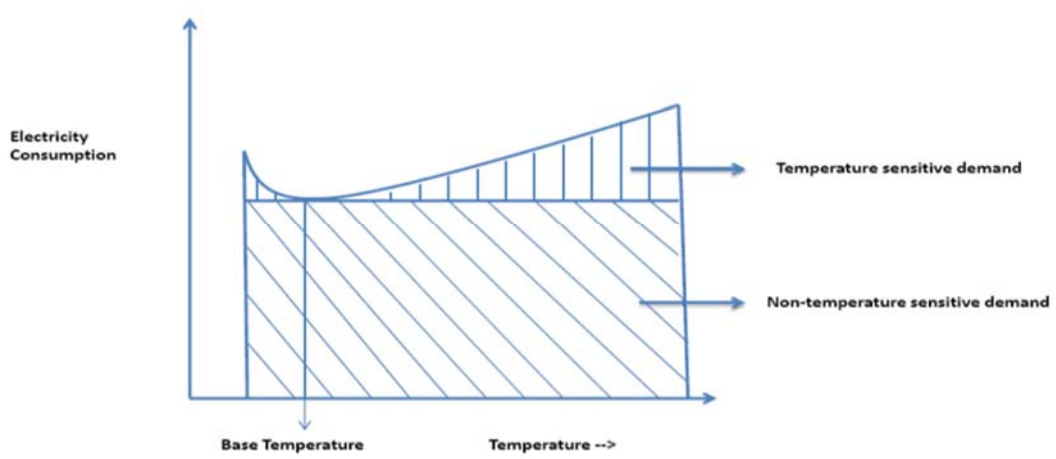
Almost all of the reviewed papers employ a surface temperature variable or its degree day derivative to model the climate effects. A few studies use other climate variables like precipitation and wind speed in a regression-based model (e.g. see Howden and Crimp (2001) & Sailor and Munoz (1996)). Temperature is usually represented by a derived unit called the degree days. The heating and cooling degree days (HDD and CDD) are employed as the key independent variable in these models. HDD or CDD is defined relative to a base temperature – the temperature which corresponds to the desired indoor settings (base temperature is usually set between 55°F to 65°F). HDD refers to the negative deviations between the average of hourly temperatures and the base temperature in a given day. CDD refers to the positive deviation of the average of hourly temperatures and the base temperature in a given day. The choice of base temperature roughly corresponds to the daily mean temperature at which electricity consumption is at its minimum. Amato et al. (2005) suggest additional factors, such as built environment characteristics, non-temperature conditions (like humidity, and precipitation) and cultural preferences, be taken into account when determining the base temperature.

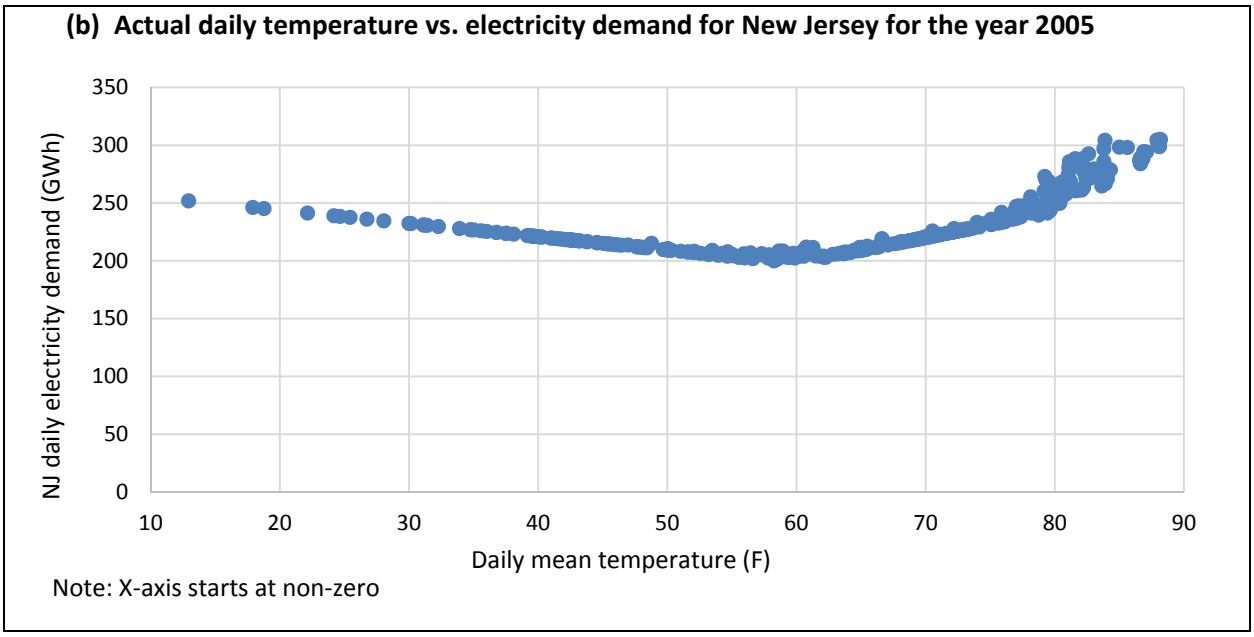
Figure 2.3(a) presents the theoretical relationship between temperature and electricity use. At the base temperature, the energy requirement is at a minimum since by definition the ambient weather conditions are the same as the desired indoor settings. The underlying assumption in a U-shaped energy demand-temperature function is that the temperature sensitive demand (TSD) is the two triangular wedges above the base consumption level, whereas the non-temperature sensitive demand (NTSD) is the rectangular

area below the base consumption level. NTSD includes energy consumed for lighting, refrigeration, industrial processes, transportation and captive power demands from generating units. The U-shaped demand response to temperature change is a consequence of the non-linear effect of temperature on system electricity demand. For example, the effect on system electricity demand for a 5°F increase in temperature from 33°F is different when compared to the effect of a 5°F increase in temperature from 80°F. Figure 2.3(b) presents the actual daily average temperature and electricity consumption trends for New Jersey for the year 2005. From the graph, the base temperature roughly corresponds to the range of 55-59°F where the system electricity demand is at a minimum. Summation of the area below the graph gives the annual electricity consumption for the state. The NTSD for New Jersey in 2005 is around 73,000 GWh (i.e. 200 GWh/day*365 days). The TSD for New Jersey in 2005 is around 11,000 GWh. On a hot summer day with a daily mean temperature of 85-90°F, the daily peak demand for the state approaches a high of nearly 300 GWh. This U-shaped temperature dependence pattern suggests that climate change is likely to have an ambiguous impact on future electricity demand levels at an aggregate global/multi-regional level, as the warming weather can reduce the heating demand and increase the cooling demand (also see Schaeffer et al., 2012).

**Figure 2.3 (a)-(b): Relationship between electricity demand and average daily temperature**

**(a) Theoretical relationship**





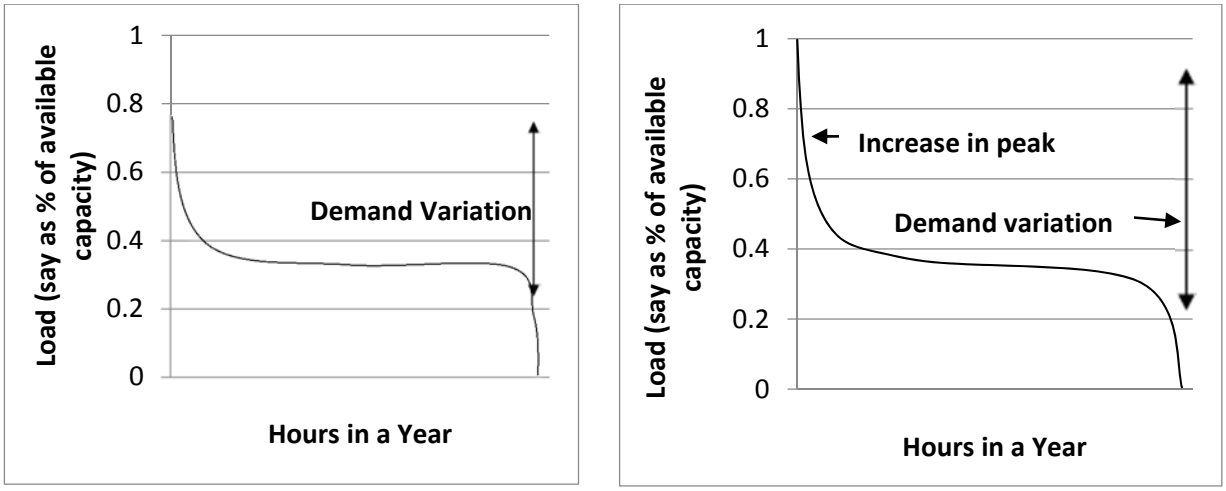

The industrial sector account for nearly one-third of the world's total electricity demand[14]. Generally, industrial energy demand is not particularly sensitive to climate change effects as most industrial processes operate at a temperature level much higher than the fluctuations in ambient conditions (CCSP, 2008). Except for Considine (2000) none of the reviewed papers have addressed the effect of climate change on industrial consumption or demand. This is partly due to the fact that industrial demand is considered to be non-temperature sensitive. Some research studies have predicted that an increase in cooling water temperature is likely to reduce the demand for water heating (Considine, 2000).

To get an overall picture of the demand variations, model developers have used the concept of load duration curves (LDCs). An LDC is a curve (see Figure 2.4) in which the load or the demand data for a given time interval is arranged in a descending order of magnitude. The point at which the curve touches the Y-axis indicates the peak system demand. The area under the curves denotes the MWh energy consumption/demand in a given time frame (usually a year). From a theoretical perspective, the effect of

[14] International Energy Agency - http://www.iea.org/publications/freepublications/publication/kwes.pdf

climate change is to increase the peak of the LDC. The difference between the peak and the off-peak demand is also expected to increase. The increase in peak load demand could have significant implications on the capacity market design and generation expansion planning (see Chapter 6 for a scoping study on market design implications). Generally, electricity systems are designed to meet the peak load demand. A sharper peaks call for increased capacity installation and availability of peaking units that runs only for a few hours in a year.

**Figure 2.4: Theoretical effects of climate change on Load Duration Curves (LDCs)**




The consistent inference from these studies is that the overall primary energy demand is expected to *increase* in the future due to population increase, economic growth and climate change effects. There is no consensus in the literature on whether there would be a net increase or decrease in overall heating demand in the coming decades. Most studies predict that a warming weather trend is likely to *reduce* the heating demand for colder regions in Europe and North America. There is no consensus in the literature on the magnitude of these effects for specific geographic regions/countries. In general, energy projections differ based on scenario, climate and other modeling assumptions. There is however a high degree of consensus among the reviewed studies on the fact that electricity demand is likely to *increase* in the future. This is due to the increase in cooling demand and rapid adoption of air conditioners in colder

regions of Europe and North America. Also, the increase in cooling demand is likely to outpace the decline in heating demand requirements. Electricity demand is often estimated in the literature as a function of heating/cooling degree days (HDDs/CDDs). Some studies have also used other climate variables like humidity and wind speed to model the effects on system demand. LDCs are perceived as good modeling tools to study the impact of climate change on electricity system demand. Table 2.3 compares the different temperature-demand model frameworks, the key parameters these models incorporate and their findings. The rationale for compiling this list is to present a snapshot of the nature and type of demand-side models found in the literature.

**Table 2.3: Summary of models focused on demand-side impacts**

| Study | Model Type | Key Parameters | Model Framework | Key Findings |
|---|---|---|---|---|
| Loveland and Brown (1990) | Computer Simulation (of heat transfer equations from a typical building) | Five representative buildings<br>Six major cities<br>Typical Year climate data from NOAA | Scope of study: Six major cities in US | Annual cooling load for buildings will increase at a much greater rate than heating loads |
| Rosenthal & Gruenspecht (1995) | Non-regression type (temperature rise is assumed)<br>Logistic regression to model probability of owning an air conditioner as a function of CDD. | Dependent Variable (DV): Energy demand<br><br>Independent Variable(IV): degree days<br><br>Scenarios: baseline and global warming scenario | Scope of study: Five typical climate zones in the US.<br><br>Energy demand projection for a 1°C rise in temperature using change in HDD/CDD in five distinct climatic zones.<br><br>Corresponding change in degree days is mapped into energy demand for space conditioning. | A global warming of 1°C would reduce projected U.S energy expenditure in 2010 by $5.5 billion (1991 dollars).<br><br>When increased penetration of air conditioners is taken into account the savings drops to $4 billion. |
| Sailor and Munoz (1996) | Multiple linear regression models | DV: Energy demand<br>Primitive variables (IV): temperature, relative humidity, wind speed.<br>Derived variables(IV): HDD/CDD, enthalpy latent days (ELD) | Scope of study: MLR model applied to eight most energy intensive states in the US.<br><br>Logarithmic linear regression was used to avoid heteroscedasticity. | Degree-day approach is best suited for electricity and temperature variable is best suited for natural gas demand models.<br>Constant term in regression equation indicative of NTSD. |
| Howden and Crimp (2001) | Multiple linear regression models | DV: Electricity demand<br><br>IV: HDD/CDD, temperature humidity index (THI), vapor pressure deficit (VPD) | Scope of study: Four cities in Australia<br>MLR model is used to determine climate sensitivity of electricity demand. | Peak demand was found to be more sensitive to increased temperature.<br><br>Joint adaptation strategies could reduce the overall peak demand. |
| Considine (2000) | Linear regression, logit models | DV: total energy demand per day<br>IV: HDD,CDD, fuel prices, income/output | Scope of Study: US | Warmer climate conditions slightly reduce energy demand and carbon emissions in the US. |

| Study | Model Type | Key Parameters | Model Framework | Key Findings |
|---|---|---|---|---|
| Sailor and Pavlova (2003) | Linear regression models (for demand)<br>Scatter plot based curve fitting for AC saturation data | DV: Electricity consumption per capita, AC saturation(city wise)<br>IV: CDD, HDD | Scope of study: Air conditioning (AC) systems saturation data for 39 cities in the U.S | Strong correlation between AC saturation and CDD.<br><br>A 20% increase in CDD can increase residential electricity consumption by 1-9% depending on cities. Residential AC consumption alone increases by 20-60%. |
| Scott et al., (2005) | Bottom-up energy accounting model (called BEAMS) | Temperature increase for regions from IPCC TAR estimates.<br>15 Building types<br>11 Climate zones<br>Building characteristics from EIA's building energy consumption data. | Scope of Study: Residential and commercial buildings in US<br><br>Incorporates adaptive responses to climate change (like energy efficiency measures) | Net energy used for space conditioning in buildings is set to reduce by 2% to 7% in 2020 for a median increase of 1.7 C across regions.<br><br>Implementing current DOE energy efficiency measures can offset the growth in building stock and increase in temperature-sensitive electricity consumption (of about 25%) |
| Mansur et al. (2005) | Multinomial logit, linear regressions | DV: Choice of fuel<br>IV: fuel price, income, Jan/June temperature, precipitation, building size | This paper estimates a multinomial discrete-continuous fuel choice model of both households and firms in order to determine the sensitivity of US energy demand to climate change.<br><br>Data: EIA's Commercial Buildings Energy Consumption Survey of 1992 and Residential Energy Consumption Survey of 1993. | Climate Change will increase energy expenditures for US households.<br><br>Increase in electricity expenditure for cooling is expected to be partially offset by decreased expenditure on heating. |
| Amato et al. (2005) | Multiple linear regression models | Energy demand (per capita per month) (DV)<br>HDD/CDD, annual trend of HDD/CDD, hours of | Scope of study: Cities in Massachusetts, US.<br><br>First step evaluates the historic temperature sensitivity of residential and commercial | Models must also incorporate the intra-annual variation in historic energy demand (using the scale of |

| Study | Model Type | Key Parameters | Model Framework | Key Findings |
|---|---|---|---|---|
| | | daylight, log electricity price<br>Scenarios: Canadian Climate Centre (CCC) & Hadley Center(HC) | demand for electricity using degree-days models.<br>Second step, uses the regression equation to predict energy usage under two sets of scenarios. | analysis on a monthly basis preferably).<br><br>Changes in energy demand to weather patterns differ by energy type (electricity, natural gas) and consumer sectors (residential, commercial), thereby highlighting the need for disaggregation in energy analyses. |
| Ruth and Lin (2006) | Multiple linear regression model (fixed effects) | DV: Electricity, natural gas and heating oil demand<br>IV: HDD,CDD, Daylight Hours, Trend variables, Log of price | Scope of study: Maryland, US<br><br>Sector: Residential and Commercial only<br><br>Uses a monthly unit of analysis on a per capita basis | Assumptions about future energy prices and population changes has larger impacts on future energy use in Maryland than assumptions about future climate projections. |
| Hadley et al. (2006a& 2006b) | Multiple linear regression models | DV: Electricity demand<br>IV: HDD/CDD | Scope of study: US census regions (including Alaska and Pacific) till 2025<br><br>Uses EIA's National Energy Modeling System (NEMS) to predict demand response to temperature increase under five scenarios. | Overall, cooling needs increases, while heating needs are reduced. In all scenario runs, there was an initial decline in energy expenditure as heating reduction outpaced cooling increase. Eventually, it resulted in an overall increase in energy expenditure. |
| Franco and Sanstad (2008) | Multiple linear regression models | DV: Electricity demand<br>IV: HDD/CDD<br><br>Scenarios: Hadley & IPCC | Scope of study: Four sites in California, US<br><br>Uses historic temperature to construct a cubic regression model. The regression estimates are used in Hadley and IPCC scenarios to estimate the impact on electricity consumption and peak demand. | Based on regression equation, the % increase (relative to baseline) in annual electricity consumption and peak demand is estimated under different scenarios. |

| Study | Model Type | Key Parameters | Model Framework | Key Findings |
|---|---|---|---|---|
| Parkpoom et al. (n.d) | Multiple linear regression models | DV: Electricity demand<br>IV: HDD/CDD, humidity, day & hour of the week | Scope of Study: Thailand (data from a regional electric utility company) | The forecasted demand profile was compared with the actual demand curve for a week in April of 2004. The curve indicates a high degree of correlation between the model forecast and the actual electricity demand data. |
| Xu et al. (2009) | Bottom-up energy accounting model | Climate projections from GCMs runs (downscaled to locations based in CA)<br>16 climate zones<br>3 IPCC scenario runs<br>16 types of commercial and residential building stock | Scope of Study: California, US<br><br>Uses a Typical Meteorological Year (TMY) approach to predict the aggregated energy consumption in buildings in 2040, 2070 and 2100 | Electricity usage under an IPCC A1F1 scenario will increase by 50% in the next 100 years.<br><br>Under a A2 scenario, the electricity usage will increase by 25% |
| Shakouri and Nadimi (2009) | Fuzzy Regression model | DV: Electricity consumption (MWh)<br><br>IV: Temperature | Scope of Study: Tehran, Iran<br><br>Uses daily temperature data to model the demand variations | Hybrid fuzzy regression models were shown to be better than OLS models |
| Zaman and Shakouri (2010) | Fuzzy Regression models | DV: Peak Electricity demand in Iran<br><br>IV: Temperature and Humidity factors | Scope of Study: Iran<br><br>Develops two fuzzy regression models: one for summer and the other for winter | Interaction of climate factors was shown to be different by seasons |

## 2.4 Models focusing on supply-side impacts

In addition to demand-side effects, numerous studies have examined the supply-side effects of climate change as well. Changes in climate variables, such as precipitation and surface temperature, could affect the supply of electricity from both thermal and non-thermal sources. From the reviewed literature, the *three* most important supply-side effects of climate change are decreased efficiency and power generation from thermal units due to elevated air and cooling water temperatures; changes in hydrological cycles and water availability for power generation; and extreme weather events and their impact on electric power infrastructure (cf. DOE, 2013 for latest assessment of energy sector vulnerabilities in the U.S). In addition to these, there are a few studies on the impact of climate change on renewable energy generation as well.

In 2010, nearly 75% of the world's electricity was generated from thermal sources like coal, oil, nuclear, and natural gas[15]. In the U.S., nearly 87% of electricity is generated from these thermal sources[16]. Warmer ambient temperature can increase the cooling water temperature, which has the potential to affect the generation efficiency of thermal power plants. As the temperature differential between the generator and the external environment decreases, the power generation efficiency reduces due elevated steam condensate temperature and turbine backpressure (DOE, 2013). In addition, increasing cooling water temperature places the thermal power plants at risk of exceeding thermal discharge limits established to protect the aquatic environment (ibid.). This could even result in frequent generation curtailments. The magnitude of these implications on specific power plants will depend on plant characteristics and site-specific temperature profiles. Durmayaz and Sogut (2006) investigates the impact of increase in cooling water temperatures on thermal efficiency of nuclear plants. Their findings suggest that a 1°C increase in ambient temperature reduces power output from nuclear plants by 0.45%. Linnerud et al. (2011) uses

[15] International Energy Agency- http://www.iea.org/statist/index.htm
[16] U.S. Energy Information Administration- http://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3

country-specific data to investigate the impact of thermal efficiency decline on different types of thermal generation technologies. The study concludes that for a temperature increase of 1°C, nuclear power output reduces by 0.8%, and coal and gas power output decreases by 0.6%. Arrieta and Lora (2004) analyses the impact of ambient temperature increase on a 600 MW combined-cycle unit in Brazil. The study finds that output of the plant varies from 540 MW to 640 MW for an ambient air temperature range of 0°C to 35°C. Changes in ambient air temperature affects power output from gas turbines as well. Davcock et al. (2004) shows a 60°F variation in temperature during a day (e.g. in a desert environment) would result in a 1-2 percentage point reduction in gas turbine efficiency and a 20-25% reduction in power output. Since the study predicts the effect to be linear, a 1°F increase in ambient temperature results in a 0.01-0.03% point reduction in efficiency and a 0.3-0.4% point reduction in power output. Since gas turbines are used as peaking units, such reductions would have a significant price impact at high peak periods. The reduced plant availability during peak demand periods would have significant implications for capacity markets as well. Although, the drop in efficiency appears negligible at a unit plant level, its cumulative supply-side impact could be very large. For the U.S., a 1% reduction in the efficiency of thermal generators due to an increase in ambient temperature is expected to result in a 25 million MWh drop in electricity supply in a given year (CCSP, 2008).

The production of electricity from thermal sources is also dependent on the availability of adequate and sustainable water supplies. Freshwater availability is expected to play a crucial role in power plant siting decisions in the future. In the U.S, thermo-electric power generation account for nearly 39% of freshwater withdrawals (US DOE, 2006)[17]. On average it is estimated that for every kWh of electricity generated,

[17] Power plants generally return most of the cooling water used. However, the discharged water is at a higher temperature compared to water drawn at source. Also, a certain portion of cooling water is consumed due to evaporation and diversion for scrubbing (around 3.3% freshwater is consumed for thermo-electric generation in the US in a given year) (DOE, 2006).

nearly 25 gallons of cooling water is required [18](CCSP, 2008. p.32). Chandel et al. (2011) use a bottom-up approach to forecast the freshwater requirement of thermal power plants in the U.S. The study computes the water requirements of major thermal power plants in the U.S based on DOE (2006) data. The study calculates the average cooling water requirement on a MWh basis for different generating technologies and configurations of cooling systems. Rubbelke and Vogele (2011, 2013) use a deterministic model for estimating the cooling water demand for power plants. Using this model, the study computes the impact of cooling water temperature on rated power capacity for plants in Europe. The interaction of ambient air and freshwater (stream) water temperatures is also modeled in this study using an empirically derived formula. The study estimates that by 2030 the available capacity of nuclear and hydro-plants worldwide will reduce by 6 GW and 12 GW respectively due to an increase in air and water temperatures, and a decrease in water availability. Vliet et al. (2012) models the vulnerability of thermal power generation to temperature increase. Unlike most of the other studies, this study uses a large sample size of over 90 power plants in Europe and the U.S. It uses the daily river flow and temperature projections from a climate model run to estimate the impact on electricity generation at individual power plants. The study shows that the existing capacity of thermal power plants reduces by 6.3-19% for Europe and 4.4-16% for United States in 2031-60 due to climate change effects. Webster et al. (2013) explores the three way relationship between water use, GHG emissions and electricity generation portfolio for Texas using a generation expansion model. This is one of the few studies in the literature that looks at the effects of climate change on the power sector expansion portfolio. The study shows that large reductions in $CO_2$ emissions from the power sector would increase the water withdrawals for electricity generation. Also, the future capacity mix under a restricted $CO_2$ scenario is not drastically different from a scenario without any such limits.

[18] It is the weighted average estimate across all technologies taking into account both consumed and re-circulated water.

However when simultaneous restrictions are imposed on water withdrawals and $CO_2$ emissions, there is widespread deployment of renewables and CCS technologies.

The major pathways through which climate change can affect hydro-power production include: changes in river flow, increased precipitation/evaporation, melting of freshwater glaciers, and changes in the capacity of reservoirs. Increased precipitation and river flow indicates a greater potential for hydroelectric generation, provided the flow does not exceed the designed capacity of the reservoir. Drastic changes to the timing of peak flow in the future is expected to affect flood control schedules and reservoir operations. There is a critical mass of published studies outlining the effects of precipitation and river flows on hydro-power generation (Lettenmaier et al., 1999; Barnett et al, .2004; Payne et al., 2004; NWPCC, 2005; Markoff and Cullen (2008); Mehta et al., 2011). These reviewed studies use a river flow variable from a hydrological model simulation run. On average, the sensitivity factor of hydro-power generation to changes in precipitation is expected to be around one[19] (CCSP, 2008). Barnett et al. (2004) estimates that the hydropower production from the Colorado River basin would decrease by as much as 40% by the middle of this century. Several of the reviewed studies like Payne et al. (2004), NWPPC (2005) and Markoff and Cullen (2008) predict inter-seasonal variations in hydropower production due to climate change effects. Winter and spring hydro-production is expected to increase, while summer production is predicted to decline considerably. Payne et al. (2004) is a good example for a comprehensive study of climate change effects on water resources of a major river basin (i.e. the Columbia River basin in the U.S). This study focuses not just on the impact on hydropower production but also on other related systems like reservoir management, flood control and marine life preservation. An EPRI (2011) study has documented the historical cases of generation curtailment due to freshwater scarcity and drought conditions. Increased

[19] A sensitivity factor of one implies a 1% increase in precipitation increases hydro-power generation by 1%

precipitation, sea level rises and storm surges increases the risk of disruption and damage to coastal energy infrastructure (primarily oil and gas facilities and coastal thermo-electric plants).

Extreme weather events have the potential to cause abrupt and unforeseen disruptions to electricity generation and supply (Mideksa and Kallbekken, 2010; DOE, 2013). Increasing intensity of storm events, sea level rise and storm surges are likely to affect operations at coastal power plants. Warmer ambient temperature in summer is expected to stress system components, such as transmission lines and transformers, due to tighter thermal limits. This also increases the chances of equipment failures and system blackouts. Miller et al. (2007) executes a comprehensive study on the effect of extreme heat days on California's electricity demand. The study predicts that the frequency of extreme heat days is expected to increase by 200% for inland cities and 400% for coastal cities in California by 2100. The study predicts a 17% electricity supply deficit for California in 2100 based on existing power infrastructure (assuming no future capacity addition and demand response/curtailment). Transmission networks are likely to be affected by increased ambient temperature, resulting in power-line sagging and reduced carrying capacity (Peters et al., 2006; Eskeland et. al, 2008). Power-line sagging poses a serious grid reliability issue and increases the chance of system outage due to power-line contact with trees and other nearby structures. With climate change, the frequency and intensity of extreme events is expected to increase in the future (see Chapter 7 for details). Such extreme weather events are also expected to affect the supply of electricity through the transmission infrastructure. CCSP (2008) reports that in 2005 hurricanes alone costs the U.S. energy industry about $15 billion. Peters et al. (2006) assess the impact of climate change on transmission networks. This study reports the average annual cost of weather-induced transmission outages in the U.S to over $2.5 billion a year from 1994-2004. With climate change, this cost may increase substantially in the coming years. Cardell et al. (2007) have proposed an incremental adaptation strategy for the power sector to respond to these extreme weather effects. They include: using long-term climate projections to estimate the rate of change of power system design parameters, developing contingency

plans to meet the challenges of extreme events, and incorporating a stochastic specification of extreme weather events in blackout risk assessments.

Climate change is also expected to affect renewable energy production from wind and solar resources. In recent years, the share of non-hydro renewables has increased considerably in the U.S. In 2013, these resources contributed nearly 6% of the total annual generation in the U.S[20]. On-shore wind is a major renewable generation technology in the U.S with an installed capacity of nearly 62,000 MW in 2013 (DOE, 2013).Unlike hydropower, wind energy cannot be stored or dispatched according to grid requirements. The energy contained in the wind is proportional to the cube of wind speed, which implies that variations in wind speed can have significant effect on power output (Pyror and Barthelmine, 2010).To add complexity to this problem, the physical effect of climate change on localized wind speed is still not clear in the literature (CCSP, 2008; Schaeffer et al., 2012). There is substantial literature on the climate change implications for wind power resources in Europe and the U.S (see Pyror et al, 2005; Clausen et al., 2007; Sailor et al., 2008; Cradden, 2010; Pyror and Barthelmine, 2010; Cradden et al., 2012). Since the share of wind resources to the overall capacity mix is low in most countries, the sector-wide impact of changing wind speed patterns is expected to be minimal in the future. Most of these studies rely on downscaled wind speed projections to estimate the localized impacts on wind power generation at major wind farm sites. Numerous studies have pointed out the pitfalls of using raw wind speed projection for estimating future energy production from wind farms. Electricity production from wind turbines depends on wind speed at the hub-height, topography of the wind farm location and also on the direction/duration of the wind patterns. Another key inference from these wind impact studies is the inter-seasonal variations in wind power generation. Wind power production is expected to decrease in summer and increase in the winter months.

[20] U.S EIA- http://www.eia.gov/tools/faqs/faq.cfm?id=427&t=3

There have been very little quantitative models or research studies on the impacts on solar energy production. We could find only two research studies on the solar energy impacts of climate change (Fidje and Martinsen, 2007; Crook et al., 2011). The two studies use localized downscaled projections of radiation flux variable to estimate the impact on solar energy production. These studies predict a possible decline in solar photovoltaic (PV) efficiency due to an increase in ambient air temperature. Fidje and Martinsen (2007) estimates that a 2% decrease in solar radiation, coupled with an increase in ambient temperature by 3.6 °C, results in a reduction in solar panel power output by around 6%. Crook et al. (2011) is more comprehensive in this regard as it includes a select group countries from different climate zones across the world. There is no consensus in the climate science literature on the magnitude or the direction of the possible changes to solar radiation metrics and cloud cover patterns (DOE, 2013. p.12). Also, concentrated solar plants (CSPs) are likely to be affected by temperature impact pathways similar to steam-based thermal units (see earlier paragraph on thermal generation impacts).

To sum up, the supply-side models have a long way to go to integrate the projections of a climate model run into a technology-specific or implication-specific assessment model. Recent assessments studies have helped to highlight the major supply-side implications: efficiency decline of thermal plants; decreasing cooling water availability for power generation and increased intensity and frequency extreme weather events (CCSP, 2008; DOE, 2013; US GCRP, 2013). But there is a clear lack of quantitative research models that could translate these implications in a manner that is of use to the policymakers. This is partly due to the uncertainty in estimating the empirical relationship between the different climate variables and electricity production. Also, as seen in the demand-side, there is little or no published literature on the supply-side implications of climate change for the developing regions and countries. Table 2.4 is a summary of the key framework of the some of the reviewed studies.

**Table 2.4: Summary of models focused on supply-side impacts**

| Study | Scale/Scope of analysis | Subject | Key Findings |
|---|---|---|---|
| Barnett et al. (2004) | Colorado, Columbia and Sacramento river basins<br><br>Uses downscaled climate projections from NCAR PCM runs from 2000-50 | Impact of climate change on water resources in the western part of US (including hydropower generation) | By 2050, the hydropower production could drop as high as 50% of the current generation due to climate change effects. |
| Davock et al. (2004) | Gas turbines-plant level analysis | Thermal efficiency of gas turbines | A 10°F rise in ambient temperature would result in 0.5% points reduction efficiency and a 3-4% reduction in power output. |
| Arrieta and Lora (2004) | Plant-level analysis<br><br>Parametric study based on ambient and exit gas temperature | Impact of ambient temperature on a combined-cycle plant in Brazil | Output of a 600MW plant varies by 75 MW for an ambient air temperature range of 0° C to 35° C<br><br>Also variations in temperature differential resulted in a decline of 150MW and efficiency drop of 3.4% |
| Payne et al.(2004) | Columbia River Basin (U.S)<br><br>Uses NCAR's PCM model projections (from 2010 to 2100)<br><br>Monthly level projections downscaled to ¼ degree resolution in the region | Impact of climate change on water resources (including hydropower production, reservoir management and marine life effects) | Significant loss in hydropower production (decline ranges from -9% in 2010-40 to -35% in 2070-98)<br><br>Temperature and precipitation changes shifts summer stream flow to winter<br><br>Hydrologic changes causes a trade-off between hydropower production and maintaining stream inflow targets |
| Pyror et al. (2005) | Baltic States<br><br>Uses RCM simulations to predict wind energy availability | Impact of wind speed on wind energy density | Wind energy density is expected to increase in the future<br><br>Increase is substantial in winter<br><br>RCM-predicted wind speeds are lower than statistical downscaling |
| Miller et al. (2007) | California<br><br>Temperature projections from GCM runs under IPCC A1F1, A2, B1 scenarios | Impact of extreme heating days on electricity demand<br><br>Uses a linear relationship of 700MW/°F increase for estimating system peak demand | The frequency of extreme heat days (defined as temperatures exceeding the "T90" metric) increases for major cities in CA. On such days electricity deficit for the state can reach as high as 17%. |

| Study | Scale/Scope of analysis | Subject | Key Findings |
|---|---|---|---|
| Fidje and Martinson (2007) | Select cities in Nordic countries in Europe<br><br>Computes the impact under different IPCC scenarios<br><br>Uses ambient temperature, snow cover deviations (i.e. 2070-2100 compared to 1970-2000) from IPCC estimates | Impact of climate change on solar energy production | Climate change is likely to have a negative impact on solar energy potential (i.e. $W/m^2$ or $kwh/m^2$ availability) |
| Sailor et al. (2008) | Unites States - Northwest region<br>Uses statistical downscaling from GCM model runs to project wind resource availability | Projecting the wind speed and density for select locations in the Northwest of US | Under a climate change scenario, wind power generation can decline by 40%<br><br>There is also an inter-seasonal effect of climate change on wind power generation |
| Rubbelke and Vogele (2011, 2013) | Models the relationship between water requirements for cooling purposes to rated power capacity subject to efficiency factors and temperature increase caps<br><br>Scope of study: Power plants in Europe | Impact of cooling water availability & temperature on thermal power generation | The study ascertains the impact of climate change on electricity supply and prices in Europe.<br><br>By 2030, nuclear power availability is down by 6 GW and hydro-power availability is reduced by 12 GW in Europe<br><br>The results confirm the need to supplement autonomous adaptation with planned public adaptation |
| Chandel et al. (2011) | United States (regional basis)<br>Scenario-based analysis till 2030 (Low and High Carbon Scenario with/ without CCS) | Freshwater use in thermo-electric generation | Freshwater withdrawal (not consumption) is set to decline by 2-14% relative to BAU (under all scenarios) in 2030.<br>At high carbon prices, retrofitting coal plants for carbon capture (CCS) increases the water use. |
| Mehta et al. (2011) | Scope: Sierra Nevada region in California<br><br>Models the impact of (+2, 4, 6 °C ) increase in water temperature for hydropower generation using historical data(1981-2000) | Impact of water temperature increase on hydropower production<br><br>Uses an Integrated River Basin Model (IRBM) | Climate change will reduce the hydropower production<br><br>Changes to regulatory approval of hydropower units must also factor the changes in future hydropower production |

| Study | Scale/Scope of analysis | Subject | Key Findings |
|---|---|---|---|
| Crook et al. (2011) | Scope: Select countries across the world<br><br>Uses climate projections from HadGEM1 and HadCM3 model runs from 2010-2080 (A1B IPCC Scenario) | Impact of solar insolation and ambient temperature on solar power production | Output from solar PV systems is set to increase in Europe and China; decrease in US and Saudi Arabia and stay flat in Australia.<br><br>CSP systems are influenced by a combination of solar insolation and ambient temperature changes. |
| Linnerud et al. (2009) | Linear Regression models<br>(one plant-specific and the other country-specific panel)<br>DV: Nuclear Power Utilization Rate<br>IV: Ambient temperature at plant sites, electricity prices (endogenous variable) | Impact of climate change on nuclear energy supply in Europe | A 1°C increase in ambient temperature reduces thermal efficiency by 0.5% (subject to a given range)<br>Droughts and heat wavers causes production loss of 2% per degree increase |
| Van Vliet et al. (2012) | United States and Europe<br><br>Adapts Rubbelke and Vogele's model on an daily basis<br><br>Uses hourly climate and rive flow projections data from 61 power plants in US and 35 in Europe | Impact of cooling water availability and temperature on thermal power generation | In 2031-60,the summer capacity of power plants is expected to reduce by 6.3-19% in Europe and 4.4-16% in United States<br><br>Extreme reductions (>90%) in rated capacity due to temperature increase is expected to increase by a factor of three in 2031-60. |
| Cradden et al. (2012) | United Kingdom (U.K)<br><br>Use two downscaled projections from two GCM runs<br><br>Uses a concept called 'geotrophic wind' and climate factor to estimate the empirical relationship between wind speed and wind energy output. | Impact of wind projections for wind energy production for U.K | High degree of uncertainty within the modeling process, selection of scenarios and estimating the empirical relationship between wind speed and wind energy |

## 2.5 Combined models focusing on both demand and supply-side impacts

Integrated Assessment Models (IAMs) simulate the complex interaction between the environment and socio-economic systems for the purpose of climate change economic assessment and policy formulation (see Kelly and Kolstad, 1998 and Peterson, 2004 for an overview on IAMs). IAMs estimate the economic effects of climate change on different sectors of the economy. Energy is a key sector for such models. Generation or Capacity Expansion Models (GEM/CEMs) are used for the capacity expansion planning problem for the electric power sector. This involves selecting the generating technology types to be added; answering the questions on when, where and the capacity of generating unit types to be added; ensuring adequate capacity resources to meet the projected future system demand and projecting the capacity and wholesale price impacts of such expansions (see Kagiannas et al, 2004 for a literature review of CEMs). In addition to these models, there are unit commitment and dispatch models (UC/DMs) used in the electric power sector. Such models are used to allocate unit commitment, dispatch electricity through the power grid, set operational reserves and compute locational nodal prices (LMPs). In general, this type of model tends to be highly granular and detailed in nature. They therefore can become computationally overwhelming to model long-term trends like climate change impacts.

This section is *not* a comprehensive review of IAMs, CEMs or the UC/DMs. Rather it focuses on energy/electricity models with different degrees of coupling to a climate model output. For consistency sake, this chapter uses the term *combined models*. A combined model is defined as a power sector model that incorporates *both* the demand and supply-side of the sector within a larger climate change assessment modeling framework. These combined models are usually constructed based on Walrasian general economic equilibrium theory. They solve a system of equations representing the demand for energy goods (such as gasoline, electricity and fuel oil) from consumers and supply of energy goods from suppliers in a given market for a given period. In most

of the models reviewed in this study, electricity is traded as an energy commodity in a highly simplified and aggregated markets. Transmission losses, network congestion and other constraints in generation or dispatch are usually ignored in these models. Many of the integrated models are in the process of development (at the time of writing). Thus, their findings or forecasts are not yet published. Hence, the scope of this section is limited to an overview of the models' architecture alone.

The Global Change Assessment Model (GCAM) is an integrated global energy-economy model. It is disaggregated into 14 geo-political regions. GCAM framework account for international trade and flow of commodities (like energy and agricultural produce) between regions (GCAM Overview, 2014).The key exogenous inputs are: population growth, estimates of GDP per capita, technological learning, externalities and discount rate. It is a dynamic-recursive partial equilibrium model with the energy system as a key component (Ibid.). GCAM has a single market for international goods (like agricultural crops and pollutant permits) and a regional market for local commodities like electricity. The price of electricity is computed on an average cost basis. The energy sector of the model analyses the demand in three end-sectors: buildings, industry and transport. The energy component of GCAM models energy resource extraction, transformation and delivery of energy goods. Electricity is one of the key modules of the energy sector. The cost assumptions are taken from publicly available estimates like EIA's Annual Energy Outlook reports. The model runs from 2005 to 2300 in five-year time steps. At every fifth year increment, the model balances the supply and demand equations for a basket of goods and commodities. The key energy output metrics are energy production (including electricity), transformation, end use, and global markets flows. It is possible to run GCAM scenarios using a preset global GHG concentration or surface temperature pathway. The GCAM projections are not predictive in nature, but can be used as a tool for understanding the complexities of interactions among the various socio-economic systems.

The Platform for Regional Integrated Modeling and Analysis (PRIMA)[21] attempts to address regional human-environment system interactions in response to climate change and uncertainties therein. The PRIMA framework consists of a suite of integrated models representing regional climate change, regional climate policy and the regional economy with specific emphasis on mitigation and adaptation measures (Rice et al., 2010). Climate projections are taken from an embedded regional climate model run. The electricity module of the PRIMA platform is called the Regional Electricity Infrastructure Framework (REIF). REIF has four major components: a Building Energy Demand (BEND), a Model of Electricity Demand (MELD), a Capacity Expansion Regional Feasibility (CERF) and an Electricity Operations Model (EOM) (Kraucunas et al., 2014). Some of the key energy interactions that PRIMA attempts to study are: the impact of climate change on energy demand under extreme conditions (e.g. heat waves); location of renewable energy production relative to energy demand centers; and implications of renewables penetration for grid operations (Rice et al., 2010.).

Golombek et al. (2011) use a multimarket equilibrium market model called LIBEMOD to study the impacts of climate change on the electricity industry. This is perhaps one of the few stand-alone combined model with an exclusive focus on electric power sector. LIBEMOD covers three important impact pathways: changes in electricity demand resulting from changes in temperature; the effect of changes in precipitation and temperature on supply of hydro-electric production; and decline in efficiency of thermo-electric generation technologies due to increases in cooling water temperature. LIBEMOD is an economic simulation of the Western European electric power sector. The model considers seven types of generating technologies or energy goods markets. LIBEMOD calculates the investment, production, trade, consumption and prices of energy goods in each of

[21] http://prima.pnnl.gov/regional-electricity-production-use

those markets. Golombek et al. (2011) concludes that the net effect of the three key partial effects is a 1% increase in average generation cost and a 4% net decrease in electricity production by 2030.

There are four important combined models that focus exclusively on U.S. energy markets (including electricity). They are EPRI's PRISM, EIA's NEMS, EPA's IPM and NREL's ReEDS models. PRISM is a regional economy-energy model of the U.S. (EPRI, 2011). The model computes parameter estimates for twelve regions in the U.S. PRISM employs a computational general equilibrium modeling approach. The National Energy Modeling System (NEMS) is an energy-economy modeling system of the U.S. through 2040. NEMS forecasts "the production, imports, conversion, consumption, and prices of energy, subject to assumptions on macroeconomic and financial factors, world energy markets, resource availability and costs, behavioral and technological choice criteria, cost and performance characteristics of energy technologies, and demographics" (EIA, 2012). Since the price, demand and type of energy resources vary across regions in the U.S., the various modules of the NEMS forecasts disaggregate data at a regional or sub-regional level. The major modules of NEMS are a demand module (for the residential, commercial, transportation and industrial sectors), a supply module (for electricity, renewables, oil supply, natural gas, refining and coal supply), an international energy module and a conversion/interaction module. The NEMS integrating module controls the entire NEMS solution process to determine whether general market equilibrium is feasible across all the NEMS modules (ibid.).

Among the reviewed models, there are two models that adopt an optimization framework (instead of the equilibrium framework). Optimization framework, in this context, refers to a linear programming approach of solving the models. The U.S. Environmental Protection Agency (EPA) relies on ICF Consulting Inc.'s Integrated Planning Model (IPM) to model the effects of air emissions from the U.S. power sector (for detailed model documentation, refer to EPA, 2012). EPA also uses IPM models to predict the power sector's response to various federal GHG emission reduction

proposals. IPM is a multi-regional linear programming model with an objective function that minimizes the power sector supply-side costs over a given planning horizon. IPM models economic activities in three key components of energy markets – fuel markets, emission markets, and electricity markets (ibid.). IPM models have been used in air regulatory assessment, integrated capacity planning, dispatch modeling and supply cost estimation. Jaglom et al. (2014) uses IPM to model the impact of increasing surface temperature on the U.S power sector. This study analyses the U.S power sector impacts due to temperature changes under two emissions trajectories- with and without emissions mitigation. It relies on a research design similar to the R/ECON-LPCEM framework. It estimates that an increase in surface temperature under a moderate emissions trajectory is likely to increase the power supply costs by about $50 billion by the year 2050.

The National Renewable Energy Laboratory (NREL)'s Regional Energy Deployment System (ReEDS) is a deterministic optimization model of the electricity sector in the U.S. (NREL, 2011). It models future generation and transmission capacity expansion. Although it is a capacity expansion model, it is designed to analyze critical power sector issues like climate change and increasing renewables penetration (ibid.). The model minimizes the capital and operating costs for the U.S electric power sector. The model determines a cost-optimal mix of generation portfolio to meet the future electricity demand. Currently, the model is capable of computing a cost minimization routine for two-year periods from 2006 to 2050. The model factors in constraints in the form of load, operating reserve, transmission, resources, emissions and policy stipulations.

**Table 2.5: Summary of combined models focusing on both demand and supply-side effects**

| Model | Developers | Key Modules | Methodology/Scope |
|---|---|---|---|
| GCAM | Pacific Northwest National Laboratory (PNNL) – University of Maryland | Primary energy, technology, energy demand, energy transformation, agriculture-land use | Global scope. Dynamic-recursive market equilibrium model. |

| Model | Developers | Key Modules | Methodology/Scope |
|---|---|---|---|
| PRIMA | Pacific Northwest National Laboratory (PNNL) | Electricity component has the following modules- electricity operations, electricity demand and electric power plant siting | Regional scope (US Midwest) |
| LIBEMOD | CREE Center-University of Oslo | Seven type of energy goods/markets | Western Europe.<br>General Equilibrium modeling |
| PRISM | Electric Power Research Institute (EPRI) | Three policy scenarios: reference case, CCS mandate, Clean energy standard.<br><br>It also considers two technology cases: limited portfolio & full portfolio. | Entire United States till 2030.<br>Analytical basis is based on LCOE calculations for various technologies. |
| NEMS | US Energy Information administration | Demand, supply, international, interaction and integrating modules | Entire United States till 2030.<br>General equilibrium modeling (for overall integrated output)<br><br>Other optimization techniques for individual modules. |
| IPA | US Environment Protection Agency-ICF Consulting Inc. | Fuel markets, emissions markets and electricity markets | Entire United States.<br>Dynamic linear programming (with cost minimization objective function). |
| ReEDS | National Renewable Energy Laboratory (NREL) | Major decision variables:<br>Renewable and conventional technology generation, storage and transmission<br><br>Parameters & Scalars:<br>Cost (operation and investment); operational parameters (like heat rate and capacity factor)<br><br>Constraints: Power flow, emissions, network constraints, technology standards(like RPS) | Contiguous United States till 2050 (in two year increments)<br><br>Deterministic linear programming<br><br>Computes wholesale prices under a rate-base and a competitive market environment |

## 2.6 Summary

An extensive review of the literature on the impacts of climate change on the electricity sector is the first step in understanding and building a combined equilibrium based or optimization models of electricity markets and systems. This review highlights the research areas where the knowledge frontier has advanced significantly, such as: temperature-sensitive demand estimation, plant-level effects of cooling water/ambient air temperature increase, supply vulnerabilities due to decreased water availability for power generation, and localized impact of climate variations on wind

resources. The research areas where the impacts remain unclear include: system-wide impact on renewables and thermal power generation, economic modeling of extreme events, vulnerabilities of transmission and coastal energy infrastructure to extreme events, long-term combined modeling at a state or regional level and the effects of climate policy and impact uncertainty on modeling outcomes. Also, there is an evident lack of scholarly literature on the climate change impacts for electric power sector in the developing regions of the world.

From the review, it is clear that the next generation of power sector impact assessment models are likely to employ multiple physical variables - such as surface temperature, precipitation, wind speed, and river flow - to model the different impact pathways. The research community can use publicly available climate datasets for modeling the climate change impacts on power sector (see Table 3.1 in Chapter 3 for a list of some of the downscaled datasets). The empirical relationships for some of the climate change implications - such as temperature effects on system demand, thermal power efficiency loss due increased ambient temperature, thermal generation curtailment due elevated cooling water temperature, precipitation impact on river flow and hydro-electric power generation - are well documented in the literature. Systematic effects of climate change on transmission and renewable resources are still unclear at this time. Integrating these documented demand and supply-side effects in a combined model framework is likely to be the next step for the modeling community. In the long run, the modeling community must also account for other types of policy and climate-related uncertainty, extreme events and other disruptive tendencies that are likely to affect the electric power sector. Also, there is a clear lack of published literature on the effects of climate change on competitive electricity market features. Electricity markets are treated as highly aggregated and simplistic in the existing combined models. There is a need for these combined models to reflect the changing policy environment, market features and transmission network characteristics at a scale that is of use to regional and national policymakers.

# Chapter 3

# Climate data and power systems planning- Opportunities and Challenges[22]

Climate change and variability have serious implications for the electric power sector. Increasing temperatures, decreasing freshwater availability, increasing incidence of extreme storm events and periodic coastal flooding is expected to affect the ability to generate, transmit and distribute electrical energy to end consumers. Recent advancements in climate data projections have opened up the possibility of incorporating climate data in power systems planning.

## 3.1 Introduction

Climate change and variability have profound implications for our energy systems. These implications are especially serious for the electric power grid with a complex and inter-connected network of generation, transmission, and distribution assets spread over a wide geographic area. Climate data is increasingly playing a critical role in planning for future electricity demand and supply. This chapter highlights the recent advancements in climate data availability and its potential use in power systems planning.

Understanding climate change and its impact on electric power systems is of increasing importance to policymakers across the world. The present increase in global atmospheric carbon dioxide ($CO_2$) is mainly due to the combustion of fossil fuels for transportation and electricity generation. In the U.S., the electric power sector is the single largest source of greenhouse gas (GHG) emissions (Morgan et al., 2005; U.S EPA, 2014). In addition, the electric power sector is also the single largest source of sulfur dioxide ($SO_2$), oxides of nitrogen (NOx), mercury, and other particulate emissions. Even with strong global efforts to mitigate greenhouse gas effects, the effects of climate change are still likely to be pronounced due to historic and extant anthropogenic emissions. Capital stock in the form of generation, transmission, and distribution assets must adapt to meet these challenges. To

[22] This chapter was published previously as a journal article. See: Chandramowli and Felder (2014b)

complicate matters, the electricity sector is burdened with assets with an economic life spanning several decades. To ensure that the electricity sector is best suited to meet the challenges of climate change and variability in the coming decades, there is a crucial need to accurately project multi-decadal trends in electricity markets and systems. Climate data from historical observations and projections from model simulations are critical in predicting and modeling the impact of climate change on electric power systems.

## 3.2. Nature of climate data and impact assessment research

Impact assessment of climate change is increasingly organized as a community-driven research enterprise. Climate data, which was once exclusively used by climate science community, is now disseminated online for researchers in diverse fields ranging from agricultural economics to wildlife conservation[23]. Needless to say, the power systems modeling community is also one of the major external research communities making extensive use of climate data for impact assessment. This wider dissemination emerged partly due to the advancements in computing networks (i.e. the Internet) and data transfer capabilities. The institutional thrust to open access and community-driven research emerged in the late 1990s under the aegis of the World Climate Research Program (WCRP). WCRP and other international partner institutions archived the results of global climate model (GCM) simulations through the Program for Climate Model Diagnostic and Inter-comparison (PCMDI)[24]. PCMDI provides an online gateway for outside researchers to access and compare the results from leading global climate models. Subsequent efforts in this direction were organized under different phases of the Coupled Model Inter-Comparison Projects (CMIP)[25] (see Meehl et al., 2005 for an overview of early CMIP phases). A major fillip to this community-driven climate change

[23] For a recent assessment report on climate change impacts on different sectors of the economy refer to the Third National Climate Change Assessment Report from U.S Global Change Research Program (GCRP). See Melillo et al., 2014.
[24] PCMDI- http://www-pcmdi.llnl.gov/
[25] CMIP: http://cmip-pcmdi.llnl.gov/

research occurred against the backdrop of preparation for the Inter-governmental Panel on Climate Change (IPCC's) Fourth Assessment Report (AR4). For the first time, the WCRP made available climate data outputs from different models and experiments well in advance of the next round of assessment report (under CMIP Phase 3) (see Meehl et al., 2007, for an overview of CMIP3). Also for the first time, a large number of multi-model climate simulations and projections were archived and made available through a unified web-based gateway for use in the wider research community. These projections and simulations contain data on global climate variables, such as surface temperature, precipitation, sea surface temperature, and heat flux, at a grid-level spatial resolution. These climate variables have a time resolution ranging from a daily to annual basis. The current phase of CMIP (Phase 5) has archived state-of-the-art multimodel climate projection datasets. These climate simulations data can be used as the basis for exploring and modeling climate change impacts and related policy issues.

More than twenty modeling institutions across the world have contributed their climate projections and simulations to this CMIP5 initiative (see Taylor et al., 2012, for an overview of CMIP5). The list of experiments and model runs were also expanded considerably in this phase of CMIP. The experiments in CMIP5 initiative are classified under two types: (1) long-term integrations (century time scale) and (2) near-term integrations (10-30 years) or decadal projections (Taylor et al., 2012). Some of key long-term experiments include: historical runs (1850-2005); standardized emissions pathways like RCP 4.5 and 8.5; a 1 percent increase in global $CO_2$ emissions a year; observed sea surface temperature (SST) and sea ice simulation; and an abrupt quadrupling of atmospheric $CO_2$. The near-term experiments focus on specific climate model forcings, processes and responses; and may not be suitable for power systems modeling application. While CMIP3 had about 36 TB of data, the CMIP5 initiative, when completed, is expected to host nearly 3.6 PB of climate data (1 petabyte

= 1,000 terabyte) (ibid.). Presently, the grid-level climate data from CMIP3 and CMIP5 are used as the basis to “downscale” climate variables at a more local level.

For simplicity's sake, we classify climate data under two broad categories: observational and projected. Observational climate data includes climate variables recorded by weather stations or satellite-based instruments. Projected or simulated climate data are obtained from general circulation/global climate model (GCMs) runs. GCMs are designed to simulate the dynamics and processes of the atmosphere and ocean. GCM projections differ based on the nature of initial conditions assumed at the start of the simulation, numerical methods used to solve the model equations, spatial resolution of the model run, and assumptions about the interaction effects of different geophysical processes (Stevens and Bony, 2013). As mentioned earlier, the climate data archived through the CMIP initiatives are usually at a grid level. For the CMIP5 initiative, nearly half of the thirty participatory models are expected to have a latitudinal resolution finer than 1.3° (Taylor et al., 2012). A grid of 1° × 1° represents a square block of 100 km on one side (or a total area of 10,000 $km^2$). Thus, climate variables at a grid level may not be of much use in power systems planning. Instead through a process of “downscaling,” the grid-level variables are projected at a much more localized scale. This process of “downscaling” involves using GCM outputs at a larger geographic scale to develop projections of climate variables at a smaller local/regional scale. One approach is “dynamic downscaling”, which involves using a Regional Climate Model (RCM). RCMs fully simulate the climate in a smaller region using data from GCMs to produce localized weather projections. Another approach is “statistical downscaling”, which uses an observed statistical relationship between small-scale climate variables (at the local level) and large-scale climate variables (at the grid level). It should be noted that CMIP initiatives usually do not publish climate data at a downscaled level. Instead several open-source initiatives have used these data to produce datasets of localized downscaled projections. Some of the publicly available downscaled datasets

are tabulated in Table 3.1. Figure 3.1 (a)–(c) is an example of a research approach that incorporates climate projections for power systems modeling.

**Table 3.1: List of publicly available downscaled projections datasets/portals**

| Dataset/Portal | Hosting Institution(s) | Data Type & Downscaling Method | Key Variables | Temporal Resolution | Spatial Resolution | Data Format |
|---|---|---|---|---|---|---|
| Downscaled CMIP3 and CMIP5 Climate and Hydrology Projections | Bureau of Reclamation & Others | Downscaled Projections from CMIP dataset<br><br>Statistical downscaling | Precipitation, Surface temperature (mean & min/max range) | Daily & Monthly basis<br><br>Years: 1950-2099. | Contiguous United States at 1/8$^{th}$ of a degree resolution (i.e. a grid with a side of 12.5 km ) | NetCDF and ASCII |
| Climate Change, Agriculture and Food Security (CCAFS) | International Center for Tropical Agriculture (CIAT) | Downscaled projections from select GCM outputs<br><br>Statistical downscaling and regional climate modeling (RCM) using a model called PRECIS | Temperature( mean, min/max range), precipitation, solar radiation, humidity, wind speed (max and mean) | Daily & Monthly<br><br>Year: 1970-2080 | Global at a resolution of 30 arcseconds to 30 arcminutes (i.e. a grid with a side ranging from 0.83km to 50km) | ASCII and ESRI-Grid |
| Ensembles Project | Santander Meteorology Group | Downscaled projections from select GCM runs (under IPCC A1B, A2, B1 scenarios)<br><br>Statistical downscaling (using linear regression) | Temperature (Min/max), Daily precipitation, Humidity | Daily<br><br>Years: 1960-2100 | Europe at a station level resolution | CSV Format |
| NASA Earth Exchange (NEX) Downscaled Climate Projections (NEX-DCP30) | National Aeronautics and Space Administration (NASA) | Downscaled projections from 33 GCM model runs under four RCP pathways | Temperature (mean, min/max) and precipitation | Monthly average<br><br>Years: 1950-2099 | Contiguous United States at a grid resolution of 30 arcseconds (i.e. 0.83 km side) | NetCDF4 |

| Dataset/Portal | Hosting Institution(s) | Data Type & Downscaling Method | Key Variables | Temporal Resolution | Spatial Resolution | Data Format |
|---|---|---|---|---|---|---|
| Regional and Global Climate | United States Geological Services (USGS) | Downscaled projections from 3 GCM model runs<br><br>Dynamic downscaling using a RCM called RegCM3 | Temperature (mean, min/max); extreme temperatures, HDD/CDD to base of 22 C; Precipitation, precipitation events, wind speed, solar radiation , wind speed and humidity | Daily, monthly and decadal | North America at a resolution ranging from a grid of size 50 km for the Eastern part and 15 km for the Western part. | NetCDF, ASCII grids |
| Regional Climate and Hydrologic Change: Internally Consistent Future Climate Projections for Resource Management | Climate Impacts Group at University of Washington & US Forest Service | Downscaled climate and hydrology data based on GCM outputs for five river basins in United States<br><br>Statistical Downscaling (delta method) | Temperature and Precipitation (average monthly totals)<br><br>Hydrological outputs (runoff and river flows ) | Monthly scale<br><br>Historical: 1916-2006;<br><br>Mid-century: 2030-2059;<br><br>End-Century: 2060-2099 | River basins in Western United States (Columbia, Upper Missouri, Upper Colorado, and Great Basins) at 1/16$^{th}$ of a degree (~6 km on side) | ArcGIS (ascii grid) |
| Climate Research Unit (CRU)/ Tyndall Center for Climate Change Research (TYN) | University of East Anglia | Downscaled projections from 5 GCM runs under different IPCC scenarios | Temperature, Precipitation, Surface pressure, Diurnal temperature range, wind speed | Monthly to daily<br>Years: 1900 to 2099 | Global (excludes ocean grid boxes) at a resolution of 1/2$^{nd}$ to 1/6$^{th}$ of a degree (i.e. a grid of side ranging from 50km to 16km) and country specific averages | ASCII, NetCDF |
| GIS Program-Climate Change Scenarios | National Center for Atmospheric Research (NCAR) | Downscaled projections from one GCM run (NCAR's Community Climate System Model) | Temperature, Precipitation | Historic Years: 1870-1999<br>Projected: 2000-2099 | United States at a resolution of 1/20$^{th}$ of a degree (a grid of size ~5km) | GIS Shapefile or NetCDF |

Note: Sources/ links to datasets are listed in the References section.

**Figure 3.1 (a)-(c): An example for power systems modeling using climate projections data: Impact of climate change induced temperature increase on Load Duration Curves (LDCs) for New Jersey (Starting from top-left: Figure 3.1 (a) to 3.1 (c))**

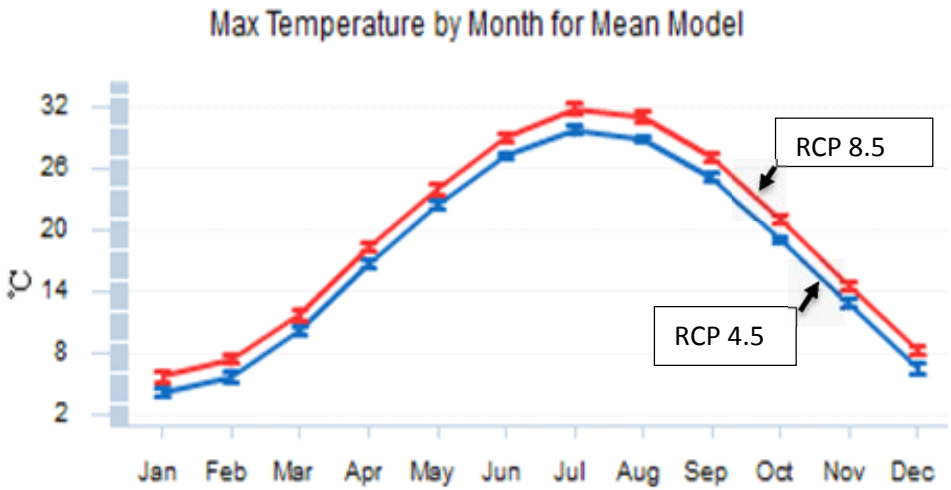
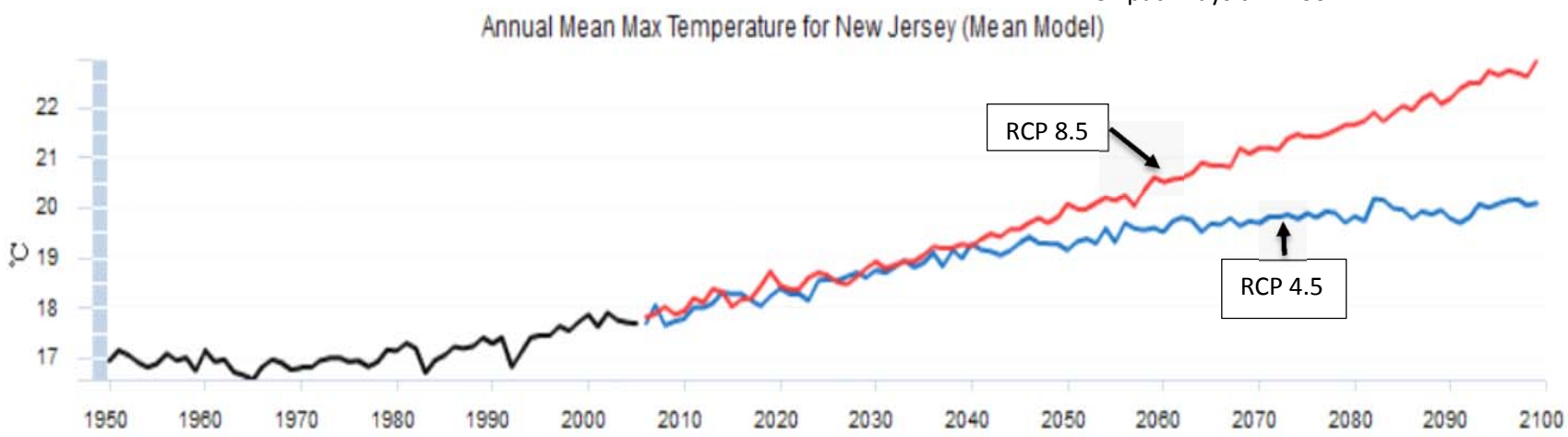



Figure 3.1: (a-b): The downscaled climate projections are derived from a publicly available NEX-DCP 30 Climate Downscaling Viewer application (Alder and Hostetler, 2013). The full NEX-DCP30 dataset includes a suite of 30 climate models and their respective downscaled data for historical (1950-2005) and future period (2006-2100) under four RCP emissions pathways. Figure 3.1 (a) on the top-left plots the mean monthly temperature for New Jersey under RCP 4.5 and RCP 8.5 projections for the years 2025-49. Figure 3.1(b) plots the changes in New Jersey annual mean temperature under two RCP pathways till 2100.



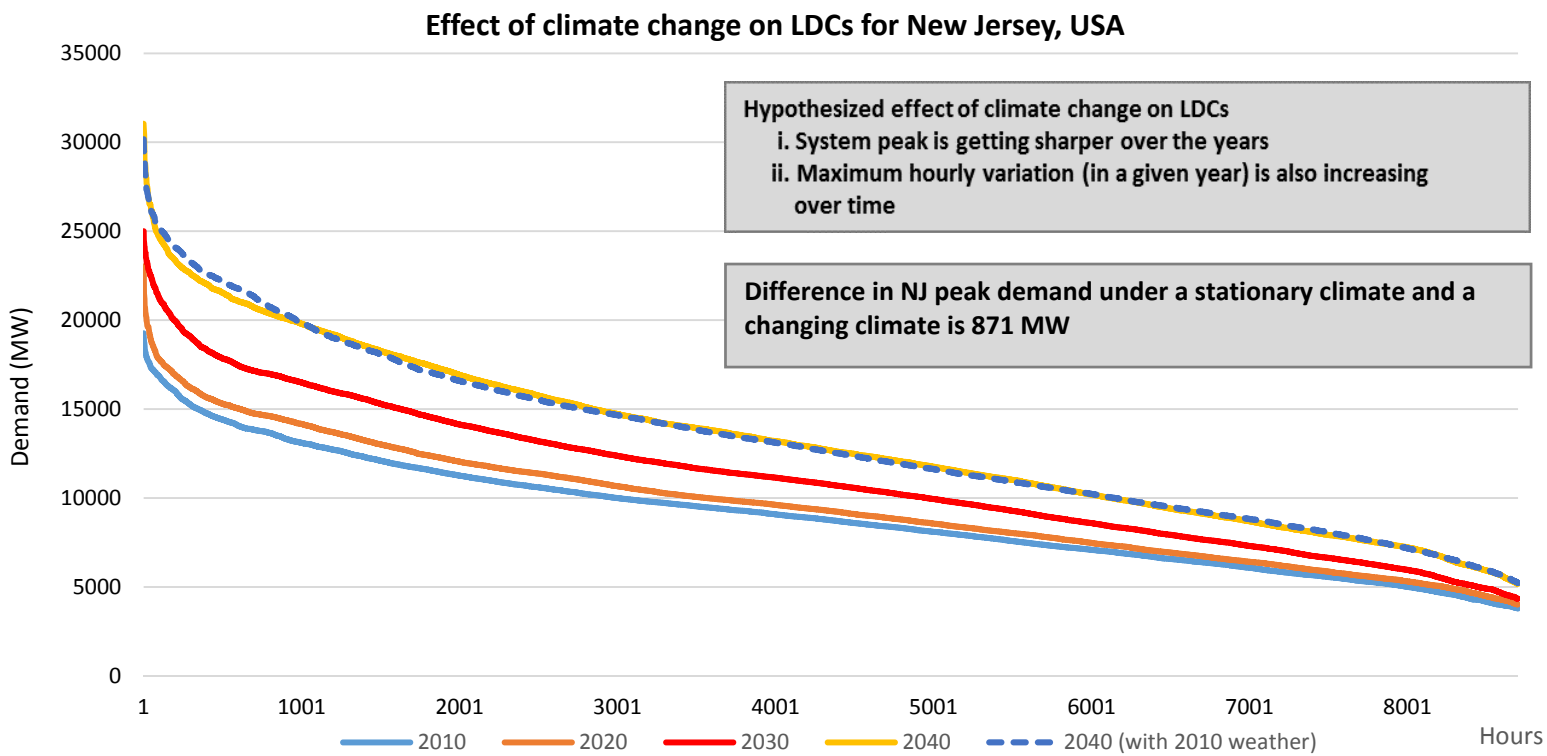



Figure 3.1 (c) presents an example of a research approach that uses downscaled temperature data to plot the changes in Load Duration Curves (LDCs) for New Jersey. The X-axis plots the hours in a typical year. The Y-axis plots the system demand (MW) arranged in a descending order of magnitude. LDCs are good modeling tool to study the impact of climate change on system demand. From the graph, we could infer that climate change and economic growth causes an *increase* in peak system demand and maximum annual variation in system demand (i.e. difference in maximum and minimum hourly demand in a year). The LDCs for New Jersey uses temperature projections at three local sites from NCAR CESM RCP 8.5 run and economic projections from Rutgers University- R/ECON-Mean simulation run. The sectoral demand (i.e. for residential, commercial & industrial) is computed based on a Weather Response Function (WRF) used by a New Jersey-based utility. The total demand is the sum of the three sectoral demand. The difference in LDCs for the year 2040, one with a temperature projection from RCP 8.5 run and the other with a historic 2010 temperature, is indicative of the effect of climate change on peak system demand.

## 3.3 Uncertainty and LP-CEM modeling framework

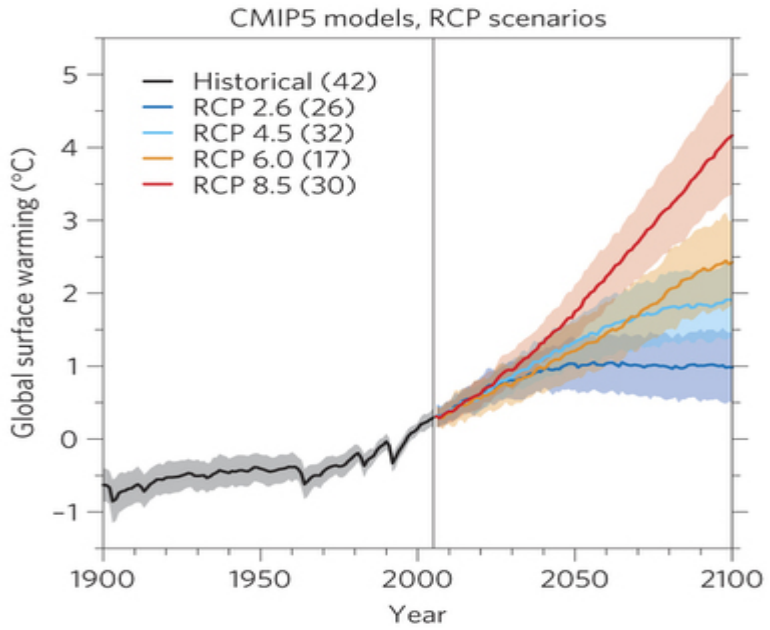
Policymakers in different sectors of the economy seek suitable climate projections data to model the climate change effects. Optimization models like LP-CEM have emerged as a key tool in long-term assessment planning for the power sector. Following the brief discussion in the previous chapter, the nature of uncertainty in a power sector assessment model is explored in greater detail in this section. Based on the current modeling trends in the literature, the next generation of power sector assessment models are likely to use multiple climate variables for modeling multiple impact pathways. With the archiving of CMIP5 datasets and numerous open-source initiatives offering downscaled projections of the future climate, opportunities for impact research on electric power systems have multiplied manifold. In recent times, a number of research studies have incorporated projections from a GCM run in a power systems assessment model (see Table 2.4 & 2.5).

For simple elucidation purposes, the uncertainty in the modeling problem can be classified under three categories: *climate, impact and policy*. The *climate* uncertainty refers to the uncertainty in projecting the future weather/climate. The *impact* uncertainty broadly refers to the unknown nature of impact pathways of climate variables to power sector parameters. The *policy* uncertainty refers to the possible policy and socio-economic settings of the future. The challenges associated with each of these uncertainty is explained in the context of the LP-CEM modeling framework. Climate/weather projections are subject to considerable uncertainty due to three distinct sources (Sutton and Hawkins, 2009). First, the *internal variability* of climate system causes natural fluctuations in future climate projections. These fluctuations are not dependent on the external forcing factor (like GHG concentration) and could be confused for the long-term climate change signal. Second, *model or response uncertainty* refers to the differences in model response to external forcing factor. The third is the *scenario uncertainty* in projecting the future state of the environment and the economy when deriving the climate projections. For the next few decades, the

climate uncertainty is dominated by internal variability and model/response uncertainty (Hawkins and Sutton, 2009).

One possible way to handle climate uncertainty is through an “ensemble” approach. An “ensemble” refers to a collection of comparable model simulations. Ensemble runs of the same climate model (GCM) with different initial conditions helps to account for internal variability in the climate system (Taylor et al., 2009; Knutti et al., 2010). Ensemble runs of different GCMs under comparable experimental design could account for the model/response uncertainty. A multi-model “ensemble” mean approach helps to filter climate change signal from climate variability noise. This “ensemble” mean can also be weighted by suitable model “weights” to account for differential model performances. The “ensemble” approach to climate projections data is illustrated for the global mean surface temperature in Figure 3.2. The CMIP5 temperature projections, under four standardized emissions pathways (RCPs), are shown in the figure. The number of models under each experimental pathway is indicated in brackets. The multimodel mean (un-weighted) projection is the thick line for each RCP pathway.

**Figure 3.2: Projected change in global mean temperature relative to a historic period (IPCC AR5)**




Source: Knutti and Sedlacek (2013)

In the current context, *impact uncertainty* refers to the unknown impact pathways of physical climate variables to power systems parameters. Consider the example of increasing surface temperature and its effect on electricity demand in the U.S. From the list of reviewed studies in Table 2.3, I could find as many as six different estimates for percentage change in electricity demand due to a unit increase in mean surface temperature. The impact pathways for other climate variables like precipitation, wind speed and solar radiation flux are still not explored thoroughly in the literature. Lastly, the *policy uncertainty* refers to plausible range of policy and economic scenarios in the future. Policy settings - such as carbon cap policies, renewable portfolio standards (RPS), tax credits, and rebates- can affect the outcome of the power sector assessment model. Likewise, the assumptions behind economic projections plays an important role in determining the system demand levels in an assessment model.

The current LP-CEM framework relies on temperature projections from the NCAR-CESM run. The temperature projections are generated under a RCP 8.5 emissions pathway. In the future, this modeling framework can be improved by using multimodel mean projection from an “ensemble” of model runs. It is also possible to run the LP-CEM for climate projections under different standardized emissions pathways. Through these improvements, climate change uncertainty can integrated into the deterministic LP-CEM optimization framework. LP-CEM attempts to account for impact uncertainty based on the best available impact pathway estimates in the literature. In the current research, we have incorporated the impact pathway of surface temperature effects on overall system demand, thermal power generation and transmission availability. This framework can be improved in the future based on advances in power sector impact assessment modeling literature and also through a better representation of impact pathways of other climate variables. The uncertainty in future state of the economy is handled through multiple scenario runs of R/ECON. R/ECON-LPCEM coupling framework is executed for three economic growth themes (Reference, High and Low growth themes) (see Chapter 4 for details). The uncertainty in future policy mix is handled through multiple simulation runs of LP-CEM. This research explores the

different carbon cap and renewable scenarios by running as many as thirty simulations of LP-CEM (see Chapter 5). Likewise, the R/ECON-LPCEM coupling framework can be executed for multiple iterations to minimize the scope of policy-type uncertainty. Limitations of uncertainty treatment in the current modeling framework and pointers for future enhancements are summarized in Chapter 7.

## 3.4 Opportunities and challenges in using climate data for power systems planning

From the review, it is clear that the next generation of power sector impact assessment models are likely to employ multiple physical variables - such as surface temperature, precipitation, wind speed, and river flow- for modeling multiple impact pathways. As of today, some of the research studies have also incorporated select demand and supply-side impacts in an economic modeling framework. Such integrated models are still at an abstract and prototypical stage (at the time of writing). In the future, it is likely that the power systems modeling community will be asked to build models that simulate the interaction of demand and supply-side effects in a manner that is of use to policymakers connected to the power sector. This requires an accurate and localized climate projections, and a robust estimate of the empirical relationship between climate variable and electric power systems. The research community can use publicly available climate datasets, some of which are listed in Table 3.1, for generating the downscaled climate inputs. The empirical relations for some of the climate change implications - such as thermal power efficiency loss due increased ambient temperature, thermal generation curtailment due elevated cooling water temperature, precipitation impact on river flow and hydro-electric power generation - are well documented in the literature. Systematic effects of climate change on transmission and renewable resources are still unclear at this time. Integrating these documented demand and supply-side effects in an integrated model framework is likely to be next step for the power systems community. In the long run, the modeling community must also account for other types of *policy* and *climate*-related uncertainty, extreme weather events and other disruptive tendencies that are likely to affect the electric power sector.

The research opportunities provided by the advent of climate data comes with its own set of challenges as well. The key challenges can be summarized under *five* points. First, the usage of downscaled climate data requires a realization that projected pathways are projections and not a prediction of the weather that is likely to occur. The climate system is a highly dynamic system capable of being influenced by a variety of geophysical and anthropogenic processes. Second, the climate data output from one model run may not capture the full extent of climate variations or suffer from a "modeling bias". The uncertainty in multi-decadal climate projections arises from two underlying sources: the internal variability or natural fluctuations of the climate system and the uncertainty in model response to different climate forcings (Hawkins and Sutton, 2009). Hence it is a recommended practice to use the average estimates of climate projections from an "ensemble" of model runs. This "multimodel ensemble" represents one of the "best effort" attempts to simulate the climate system (Taylor et al., 2012). Many of the downscaled climate data sources (listed in Table 3.1) can generate the "multimodel ensemble" projections of climate variables under different experimental designs. The number and choice of model runs to include in the "ensemble" or the choice of the averaging methodology (i.e. simple or weighted-average) depends on the specific impact that is studied and the resolution of the climate data. Third, as mentioned before, climate projections are not specific predictions of future climate. These projections are generated under a set of scenarios. These scenarios or pathways reflect various plausible futures. Hence, impact analysis of power systems must carefully articulate the reasons for choosing a given scenario and also explain the key assumptions behind it. In addition to climate assumptions, the impact studies usually incorporate socio-economic and technological assumptions to constitute a complete scenario. Fourth, there are the issues and considerations with "downscaling" and resolution of climate data in relation to the impact that is studied. Even a fine "downscaled" resolution of $1/8^{th}$ of a degree constitutes a grid of size of 156 sq. km. While a temperature variable at such a resolution may be useful to estimate the electricity demand for a city or a region, it may not be sufficiently granular to model/simulate transmission line sagging or

disruption. Hence it is important to ascertain the scale and scope of the impact to be analyzed in relation to the resolution of climate data that is available. Finally, existing climate projections do not capture any kind of disruptive climate tendencies like cyclonic storms and tornadoes (unless it is stochastically specified in the experimental design). These localized extreme events could inflict severe damage to power systems assets. Hence, researchers must be aware of the limitations of downscaled projections when attempting to use climate data in power sector assessment modeling. In spite of these challenges, climate data is poised to make a substantial contribution to power systems planning. The success of the open-source climate data initiatives depends on the quality of research it enables in the wider research community. The ultimate success of community-driven climate change impact research depends on synergetic integration of climate data into the assessment modeling framework for different socio-economic systems.

# Chapter 4

# LP-CEM: A modeling tool for power systems expansion incorporating climate change and macroeconomic effects

The electric power sector is highly vulnerable to climate change, yet long-term capacity expansion models often fail to take into account for it. This chapter presents an overview of LP-CEM (Linear Programming based Capacity Expansion Model), which incorporates both the effects of long-term warming and the state/regional level macroeconomic trends. We apply the modeling framework for the electric power system in New Jersey, United States. Some of the methodological advances introduced in this research are: the use of high-resolution temperature projections data in a power sector capacity expansion model; the incorporation of changes in sectoral composition of electricity demand over time; the incorporation of the effects of climate change and variability on both the demand and supply-side of power sector using parameters estimated in the literature; and an inter-model coupling link with a macroeconomic model to account for price elasticity of demand and other effects on the broader macro-economy. LP-CEM-type models can be of use to state/regional level policymakers to plan for future mitigation and adaptation measures to climate change. Scenarios with climate variability, climate change effects and with high economic growth rates result in *higher* capacity additions, supply costs, wholesale/retail prices and total ratepayers' costs.

## 4.1 Introduction

Climate change poses a serious threat to human welfare (Hansen et al., 2013; IPCC, 2013; Mellilo et al., 2014). Some of the key environmental effects of climate change are: rise in global surface temperature, changes to hydrological cycles, ocean acidification, rise in mean sea levels and higher incidences of extreme weather events (like storm surges, heavy precipitation and heat waves) (Mellilo et al., 2014).The environmental implications of climate change are especially serious for the electric power sector, which oversees a complex and inter-connected network of generation, transmission and distribution assets spread over a wide geographic area. The motivation for incorporating climate change effects in long-term power systems planning is grounded on three factors. First, the electric power sector is the single largest emitter of $CO_2$ and other pollutants like $SO_2$, NOx, mercury and particulate emissions (Morgan et al., 2005; EPA, 2014). Hence any kind of future mitigation or adaptation effort must have a prominent focus on the electric power sector (see Felder (2014) for global implications of mitigation efforts on energy systems).

Secondly, a transition to a low-carbon economy requires a rapid de-carbonization of the current power generation portfolio. Fripp (2012) and Clemmer et al. (2013) are examples of research studies motivated by this transition aspect of climate change implications. Although this chapter does not address this transition directly, the current set of business-as-usual (BAU) scenario runs furnish a quantitative estimate of the increased power supply costs due to future changes in generation portfolio. Finally, the electric power sector is burdened with assets with an economic life spanning several decades. To ensure that the electricity sector is best suited to meet the challenges of climate change and variability in the coming decades, there is an urgent need to accurately project the multi-decadal trends in electricity markets and systems.

In this chapter, we describe a generation/capacity expansion model (GEM/CEM) at a state/regional scale that incorporates the multi-decadal effects of a changing climate and an evolving macro-economy. To accomplish this objective, we use a linear programming based CEM (hereafter referred to as LP- CEM). GEM/CEMs are used to solve the capacity expansion planning problem for the electric power sector. This involves selecting the type of the generating technology to be added to the system; determining the capacity of the generating unit type to be added and the time period at which these capacity additions should take place; ensuring adequate capacity resources to meet the projected future system demand and operating reserve requirements; and projecting the capacity and wholesale price impacts of such expansions on the ratepayers. LP-CEM uses a supply-side cost optimization framework to derive the least-cost expansion plan. An overview of the overall research pathways, the model architecture, scenario definitions and key results from model runs are explained in the following sections.

## 4.2 Literature review and contributions

GEM/CEMs have been extensively studied in the literature (see Kagiannas et al. (2004) for a review of GEM/CEMs). These models are predominantly used in the context of a systems engineering approach to

the capacity expansion planning problem. In recent times, these models have been extended to analyze different policy implications relating to the electric power sector. Some GEM/CEMs are also used to project the optimal deployment of intermittent renewable resources. Some of the recent peer-reviewed research studies using a GEM/CEM modeling framework for extended policy analysis is listed in Table 4.1.

**Table 4.1: A summary of recent peer reviewed studies using a GEM/CEM for extended policy analysis**

| **Study** | **Key policy implication studied** | **Modeling Approach** |
|---|---|---|
| Jaglom et al., 2014 | Modeling the impact of rising temperature on the U.S power sector | Uses EPA-ICF Consulting's Integrated Planning Model (IPM), a dispatch and capacity expansion model, to analyze the impacts in terms of supply costs, electricity prices, $CO_2$ emissions and energy expenditures. |
| Mai et al., 2014 | Modeling a high renewable electricity penetration in the US | Uses NREL's Regional Energy Deployment System (REEDS) (a linear cost optimization model), to study the capacity expansion under a high renewable energy mix |
| Logan et al., 2013 | Modeling natural gas scenarios for the U.S power sector | Uses NREL's REEDS, to study the future trends in capacity expansion under different natural gas price scenarios |
| Webster et al., 2013 | Water- $CO_2$ emissions tradeoff in generation expansion planning | Uses a mixed integer linear program for Texas ERCOT region for the year 2050 |
| Hu and Jewell, 2013 | Generation expansion with integration of variable renewables and bulk energy storage systems (modeled as an virtual transmission line between time periods) | Uses an optimal power flow (OPF) based multi-period linear optimization model for a test bus |
| Clemmer et al., 2013 | Modeling low-carbon electricity futures to study the impacts on water use | Uses NREL's REEDS to model a range of low-carbon scenarios for the U.S |
| Fripp, 2012 | Generation expansion planning with large scale penetration of renewables | Uses a multi-period stochastic linear programming model (called SWITCH) for California (2012-2027) |
| Bird et al., 2011 | Impact of renewable portfolio standards(RPS) and cap-and-trade on U.S electricity sector | Uses NREL's REEDS to model a range of policy scenarios for the U.S |
| Chen et al., 2010 | Generation expansion planning towards a low-carbon economy | Uses a linear supply-side cost optimization for China from 2011-30 with carbon costs imposed on fossil-fuel generation |
| Lucena et al., 2010 | Generation expansion planning for Brazil under different climate change scenarios (using downscaled climate projections) | Uses a long-term optimization model (called MEAD-MESSAGE) to examine the possible adaptation pathways for Brazil |

| Study | Key policy implication studied | Modeling Approach |
|---|---|---|
| Linares et al, 2008 | Incorporating oligopoly, $CO_2$ emissions trading and green certificates into generation expansion model | Formulates a Mixed Complementarity Problem (MCP) for each supply-side firm/ generating technology and solved for Spain |
| Yu, 2008 | Impact of charging profile of plug-in hybrid vehicles(PHEV) on generation expansion | Uses EIA's National Energy Modeling System (NEMS) equilibrium model to project the capacity expansion for the US under different scenarios till 2030 |

Nearly all of the reviewed studies use a GEM/CEM framework to model the mitigation and adaptation efforts undertaken by the electric power sector to climate change and variability. A majority of the reviewed studies have relied on large-scale models of the power sector developed at research institutions for quantitative policy analysis (like NREL's ReEDS, EIA's NEMS, IAEA's MESSAGE and PNNL's REIF)[26]. The rest of the reviewed studies have used custom-built models to draw policy inferences about climate change effects on the power sector. Except for Jaglom et al. (2014), none of the reviewed studies have attempted to model climate change effects on the demand and supply-side in an integrated manner. Here we attempt to model climate change induced effects on both the demand and supply-sides of the electric power sector and integrate them in a supply-cost optimization framework. In addition, we have also coupled the LP-CEM model to a detailed macroeconomic model of New Jersey. The rationale for this inter-model "coupling loop" is explained in Section 3.1. LP-CEM is used to investigate the overall societal cost of climate change effects for New Jersey ratepayers for the years 2013-2040. To do so, the model also incorporates recent estimates of capital and operating costs of power plant units; anticipated trends in

[26] NREL-National Renewable Energy Laboratory (see Short, 2011 for ReEDS description); EIA-Energy Information Administration (see EIA (2013 a) for NEMS overview); IAEA- International Atomic Energy Agency (see Lucena et al. (2010) for model overview). PNNL- Pacific Northwest National Lab (see Kraucunas et al., 2014 for REIF overview). Regional Electricity Infrastructure Framework (REIF) is an upcoming suite of models focusing on electric power sector and its links to other environmental and economic systems.

generating technologies; transmission, operating reserves and other technical constraints; and near-term energy policies, regulations and mandates that will have an impact on the future generation portfolio.

This chapter's contribution to this broad body of literature on GEM/CEMs is *twofold*. First, it is one of the few studies in the literature to integrate the climate change effects in both the demand and supply-side using "downscaled" climate projections. We could find only three other peer-reviewed studies that have integrated a detailed climate input into a capacity expansion model (see Lucena et al., 2010; Taseka et al. ,2012; Jaglom et al., 2014). LP-CEM uses detailed hourly temperature projections data to model the changes to system demand. Likewise the constraints to generation and transmission are modeled based on parametric estimates of climate change effects. These changes are integrated and modeled as constraints in a linear optimization framework. Secondly, none of the other reviewed studies have coupled their input or output to a regional or state-level macroeconomic model. To accomplish this objective, this research uses R/ECON[27], a detailed macroeconomic model for the state of New Jersey. Through this inter-model coupling, the price elasticity of electricity demand and projected electricity price changes on other sectors of the economy are captured in the modeling framework. R/ECON projects the changes to retail electricity prices and the sectoral composition of electricity demand (i.e. Residential, Commercial and Industrial) over a thirty-year period. LP-CEM uses these inputs to compute the trends in wholesale/retail electricity prices and capacity expansion under a climate change scenario with different growth rates for the economy. To provide a comparative basis for these estimates, the model outcomes are compared to a scenario that does not incorporate climate change impacts. LP-CEM is configured to model the whole of the Northeast of United States. The rationale for this arrangement is that electric power grid is interconnected by means of transmission networks, and those networks do not match the

[27] R/ECON™ is a quarterly structural econometric time-series model of New Jersey. It consists of over 250 equations that estimate, among other things, state GDP, personal income, inflation, energy prices, demand, unemployment, local and state tax revenues etc. - http://policy.rutgers.edu/cupr/recon/about.php

geographic boundaries of the states. Also, it is often the case that capacity resources in a nearby network/state could serve the demand in one particular state, i.e. the demand in New Jersey can be supplied by generation resources in the wider region/network. For coupling purposes with an economic model, this chapter restricts the discussion of results to New Jersey alone.

## 4.3 Research methodology

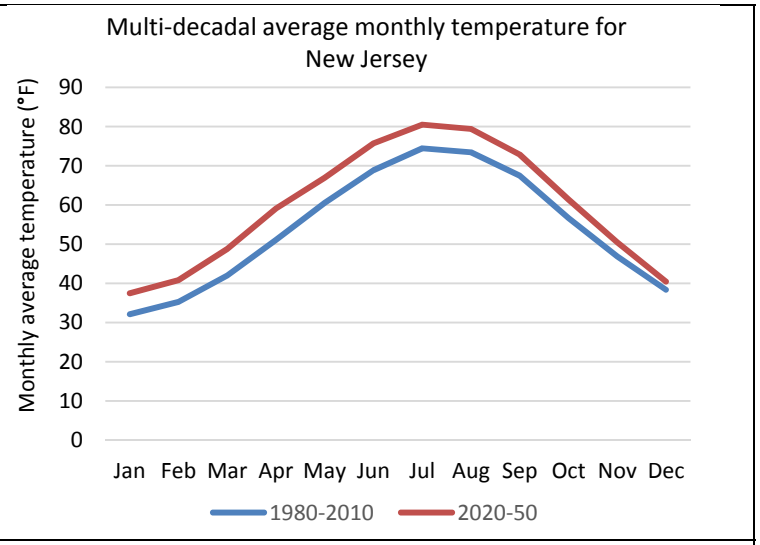
### 4.3.1. Temperature projections from NCAR-CESM simulation run

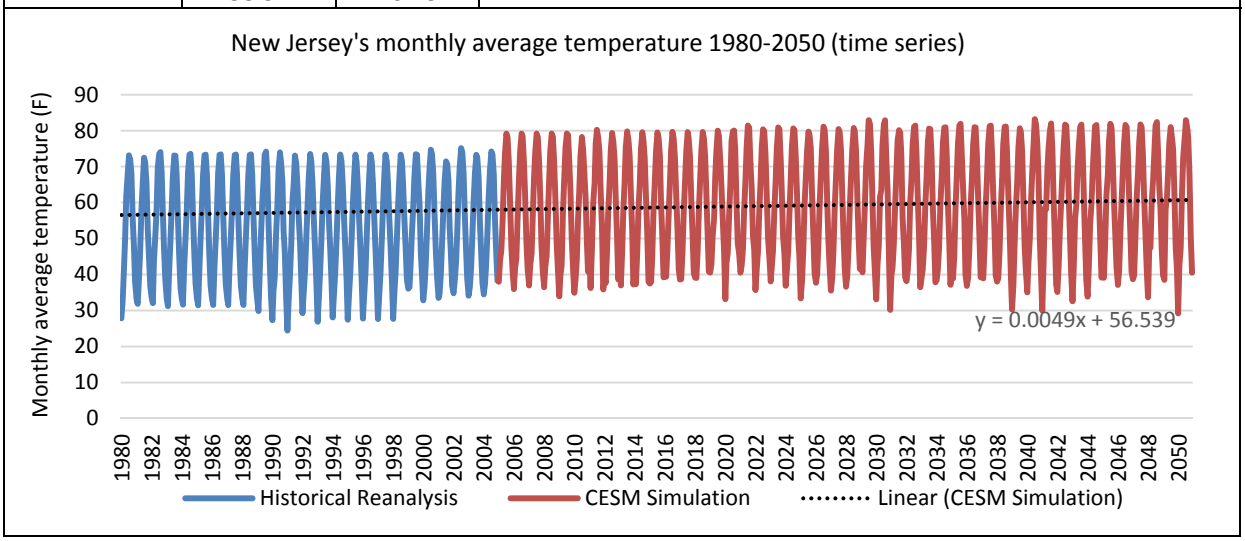
The LP-CEM definition of "system" encompasses the electric power system in the U.S. Northeast region. Broadly this includes the network of physical assets used in the generation, transmission, distribution and use of electricity. This system is subject to different climate change and economic growth perturbations. The climate change perturbation is in the form of temperature projections for three local sites in New Jersey. Climate data can be broadly classified under two types: observational and projected (see Meehl et al., 2007; Overpeck et al., 2011; Taylor et al., 2011; Chandramowli and Felder, 2014a for an overview of recent climate data advances). Observational climate data includes the actual climate variables recorded by weather stations or satellite-based instruments. Projected or simulated climate data are obtained from general circulation/global climate model (GCMs) runs. GCM projections differ based on the nature of initial conditions assumed at the start of simulation, numerical methods used to solve the model equations, spatial resolution of the model run, and assumptions about the interaction effects of different geophysical processes (Stevens and Bony, 2013). For the current modeling effort, we rely on a high emissions pathways known as Representative Concentration Pathway 8.5 (RCP 8.5) (see Moss et al., 2010; van Vuuren et al., 2011). RCPs are standardized emission pathways used in climate change impact studies. LP-CEM uses temperature projections from National Center for Atmospheric Research (NCAR)'s Community Earth System (CESM) model runs (NCAR, 2014). For this research project, a regional version of CESM was executed with an adaptive grid on the Mid-Atlantic region. CESM outputs are calibrated to historical observations till the end of the year 2004. The simulated runs are used to predict the climate

variables from 2005 till 2050. Among the climate variables simulated by CESM model run we use temperature projections at three local sites in New Jersey. These sites are assumed to be representative of the weather patterns in the state. Figure 4.1 denotes the average of the temperature trends for New Jersey under a RCP 8.5 emissions pathway. For the years 1980-2050, the average annual temperature for the state increases by 0.058 °F/yr. The current set of model runs do not consider other climate change effects like precipitation changes, coastal inundations and other disruptive climate tendencies (like changes in frequency/severity of extreme events).

**Figure 4.1: Localized monthly-average temperature trends for New Jersey (from NCAR CESM)**

| Temp (°F) | 1980-2010 | 2020-50 |
|---|---|---|
| Jan | 32.13 | 37.49 |
| Feb | 35.26 | 40.81 |
| Mar | 42.01 | 48.77 |
| Apr | 51.11 | 59.10 |
| May | 60.54 | 66.95 |
| Jun | 68.87 | 75.73 |
| Jul | 74.46 | 80.51 |
| Aug | 73.42 | 79.41 |
| Sept | 67.47 | 72.86 |
| Oct | 56.66 | 61.39 |
| Nov | 46.86 | 50.47 |
| Dec | 38.37 | 40.48 |



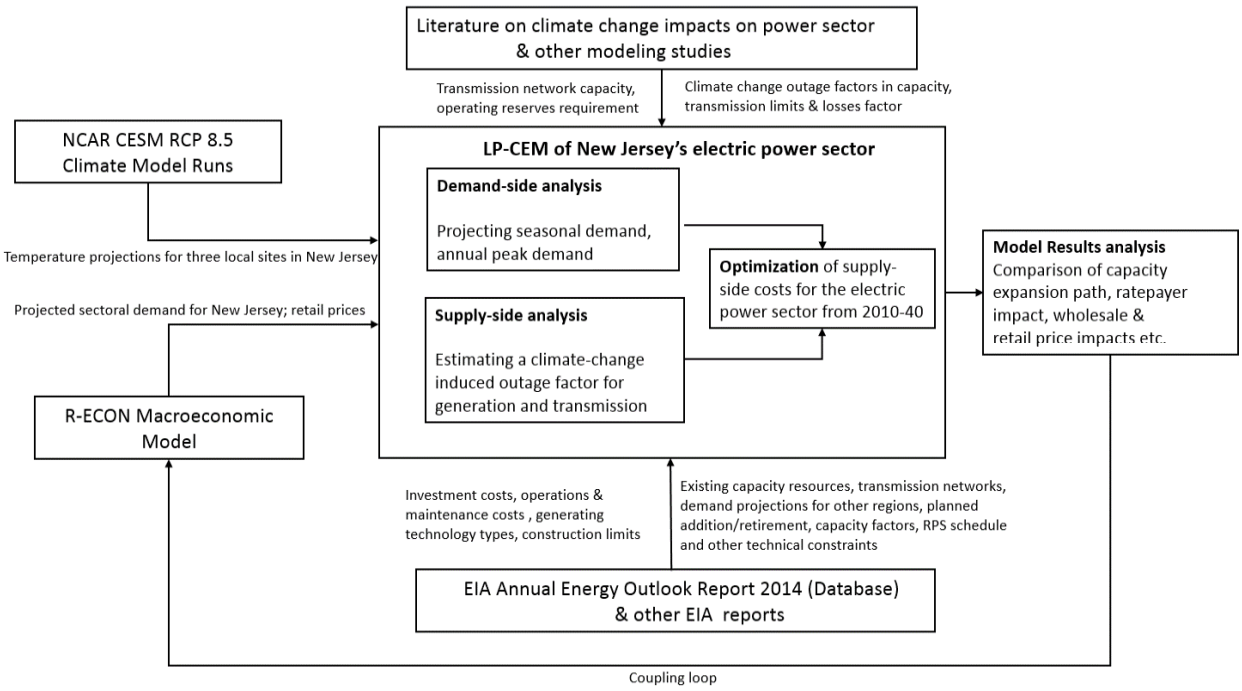
### 4.3.2 R/ECON model inputs

The second major perturbation to the system is the different macroeconomic trends for the corresponding simulation period. The R/ECON™ Econometric Forecasting Model is a highly detailed model of the New Jersey economy. The model is specific to New Jersey, and consists of nearly 300 equations covering all major sectors of the state's economy. The equations are based on historical time series data for New Jersey and the nation. The model forecasts a full range of macroeconomic variables including gross domestic product, prices, personal income, population and labor force, and state tax revenue. It also has energy, real estate, and motor vehicles sectors. The model is used for both forecasting and policy impact analysis. The R/ECON model has six key sectors: (1) the industrial sector, including employment, gross domestic product of New Jersey (GDP), wage rates, and price deflators for major industries; (2) the personal income sector; (3) the population and labor force sector; (4) the state tax revenue and expenditure sector; (5) an energy sector for the electric and gas utilities and for fuel oil; and (6) an "other" sector which includes equations for real estate and construction and motor vehicles.

R/ECON projects the macroeconomic trends for New Jersey under three pathways: R/ECON Mean, High Growth and Low Growth. These R/ECON pathways have different growth rates for macroeconomic variables such as state Gross Domestic Product (GDP), unemployment rates, energy demand and personal income. The R/ECON model assumes the following average annual growth rates in real GDP for 2010-2040: Reference (2.24%), High Growth (2.28%) and Low Growth (2.20%). Combining these pathways with RCP 8.5 climate projections and climate change effects, results in a matrix of six scenarios (a detailed account of the scenarios is presented in the following section). The data pathways in this analysis are represented graphically in Figure 4.2. The results from the LP-CEM simulation run are fed back to the R/ECON model to complete the inter-model "coupling loop". In this research, this "coupling loop" is executed for one complete iteration. As a result of this "coupling loop", the demand and retail price projections are revised and fed back into the LP-CEM model. For the reference scenario theme, this

feedback effect from R/ECON model results in a cumulative demand increase of 0.34% for the years 2013-2040 and a decrease in average annual retail price by 0.02%. This "coupling loop" can be continued until a convergence is achieved in key economic-electric power sector parameters.

**Figure 4.2: Analytical framework for incorporating climate change effects and macroeconomic trends into LP-CEM**




### 4.3.3 LP-CEM Model- Overview

LP-CEM is a long-term capacity expansion model that minimizes the supply-side costs of delivering electricity to the Northeast region from 2010-2050. The supply-side costs include the energy generation costs from dispatching units; operations and maintenance costs of all operating units, investment costs of new units and transmission costs incurred in meeting the system demand. The Northeast region covers the states in New England region, New York, New Jersey, Pennsylvania, Maryland and Delaware. LP-CEM operates on a seasonal time resolution in a given year (i.e. summer, winter, spring and fall). In addition, demand estimates are also distributed into off- and on-peak periods for each of the four seasons (resulting in a total of eight demand periods). The model uses a real discount rate of 6.5% to reflect the long-term market rate for capital in the power sector. The cost minimization is also subject to a large number of

constraints, including: balancing electricity supply and demand at a given time period; installing capacity resources to meet the operating reserves margin; transmission network constraints; transmission losses; satisfying the generation characteristics of each technology type and ensuring future capacity additions satisfy the resource potential and construction limit constraints. In addition to these technical constraints, there are the policy-type or scenario-specific constraints like minimum renewable generation requirement, construction limits on power plants; cost factor for investment and operations and fuel costs trends. Electricity demand, generation and operations costs, existing capacity and transmission capacities are exogenously specified in the model. The model does not take into account transmission expansion during the simulation period. Also, LP-CEM does not factor in trade with regions outside of the Northeast. Distributed generation, energy efficiency targets, demand response and energy storage are not assumed for the current set of baseline model runs. There are three key decision variables in the model: amount of capacity to build (in MW); power generation (in MWh) from available capacity resources and the amount of power to be transmitted (MWh) between sub-regions in the model. The wholesale and capacity prices of electricity are obtained as the dual of the demand and capacity constraints (see Rau, 2003; Short et al., 2011). The dual price reflect the competitive wholesale market price of electricity corresponding to the overall system demand and other technical constraints. The model formulation is summarized in Figure 4.3. The model is solved in GAMS using CPLEX solver with a run-time of around 3-4 minutes for each scenario run.

**Figure 4.3: Simplified representation of the LP-CEM architecture** [28]

**minimize** (Net present value of the total supply-side costs (i.e. Investment costs+ O&M costs + Fuel costs + Transmission costs)

subject to the following set of constraints

- Total system demand + Operating reserve + Transmission losses = Total MWh Generation
- MWh generated in a time period = (Initial Capacity - Retirement + New Investments) x Availability factor x Climate Change Outage factor x Hours in a time period
- Net available capacity ≥ Peak demand+ Reserve margin
- Inter sub-region transmission(MWh) ≤ Transmission capacity(MWh) for respective links
- MWh generation from renewable sources ≥ RPS limit for a given sub-region and year
- New renewable MW addition ≤ Renewable energy potential(MW) for each sub-region
- Capacity addition of nuclear and new generating technology types is permissible beyond a predefined waiting period (to account for technical feasibility)

### 4.3.4 Key Input Assumptions

LP-CEM autonomously identifies the timing, the type and the quantity of new generation resources that must be built to satisfy the projected system demand and the technical and policy constraints. The list of possible generation technologies that could be built in the simulation runs include: coal (conventional and advanced), combined cycle (conventional, advanced and advanced with sequestration), combustion turbine (conventional and advanced), nuclear, geothermal, biomass (boiler type), wind turbine (on-shore and off-shore), solar photo-voltaic (PV), solar thermal, and hydro-generators (including pumped storage). The cost and performance assumptions for different generating technology types are obtained from Energy Information Administration's Annual Energy Outlook 2014 (EIA-AEO, 2014).This includes assumptions about the type of generating technologies available presently and in the near-term future, fuel costs, overnight investment costs, operations and maintenance (O&M) costs and capacity factors of generating technologies. The cost and performance data for the current set of model runs are derived primarily from the Reference Case scenario of AEO-2014 report. For some of the scenario runs used in this

[28] A detailed mathematical formulation of the model is presented in the Appendix.

chapter, the growth estimates are also sourced from the High and Low Economic growth scenario used in AEO-2014 (the scenarios are explained in the following section).

The key characteristics of available generation technologies are shown in Table 4.2. The generating units are subject to technology-specific availability factors (based on Tidball et al., 2010). This represents the highest possible capacity factor for each generating technology. Investment costs are assumed to decline over the years based on a minimum learning factor (LR) estimate used in the AEO-2014. Both existing and new units also incur fixed and variable operating and maintenance (O&M) costs. Fixed O&M costs include expenses incurred at a power plant that do not vary significantly with the amount of MWh generation (e.g. expenses like salaries of personnel, depreciation costs of assets, facility maintenance, administrative expenses). Variable O&M costs includes expenses that vary with the amount of power generated at the plant (e.g. cost of cooling water supply, chemicals used in scrubbing equipment, lubricants used in machinery, wastewater disposal) (see EIA-2013 for a detailed list of cost factors). In addition to these costs, fuel costs are also incurred by applicable units. The costs estimates for different fuels on a $/MMBTU basis are based on the AEO-2014 report (i.e. unit cost for coal, natural gas, distillate fuels and wood biomass). The fuel cost escalation rates are based on the RECON projections for the respective scenario themes. Investments in conventional generating technology types are not subject to any kind of technical/ economic potential cap. The renewable energy investments (in MW) are capped based on the technical potential estimated for states in the Northeast region in Lopez et al., 2012. The technical potential for grid-interactive geothermal and concentrated solar power is estimated to be zero for the Northeast region (also see Tester et al., 2006). The investment costs are also subject to a regional adjustment factor to account for the interstate cost variations of constructing a new power plant.

The model account for three major pollutants from electric generating units: carbon dioxide ($CO_2$), sulfur dioxide ($SO_2$) and oxides of nitrogen (NOx). Currently, the caps imposed by EPA's Acid Rain Program for $SO_2$ and NOx are higher than the power sector emissions from the Northeast region. Hence the NOx and

$SO_2$ caps are not binding for the current set of LP-CEM simulation runs. Also, the annual $CO_2$ emissions from the power sector are not subject to any kind of cap in the model. This assumption for $CO_2$ emissions reflects an emissions pathway that is likely to occur in the absence of any future mitigation policy or regulatory constraints on a regional or national scale. The existing MW capacity for the sub-regions in the Northeast for year 2010 is based on EIA's state-level database (Form 860/923 for the year 2010) (EIA, 2013a). The existing capacity is the same for all six scenario runs (see Table 4.3). This data was also confirmed with the AEO-2014 database to ensure that the generation resources are distributed appropriately within the sub-regions.

**Table 4.2: Key input characteristics of generation technologies (for the starting year 2010)**

| Type | Availability Factor | Overnight Investment Cost (2012 $/kW) | Fixed Operating & Maintenance Cost (2012 $/kW-year) | | Variable O&M Costs (2012 $/MWh) | Fuel Costs (2012 $/MMBTU) (in 2010) | Heat Rate (BTU/kWh) | |
|---|---|---|---|---|---|---|---|---|
| | | | Existing | New | | | Existing | New |
| **Coal** | 0.75 | $ 3,246 | $ 48.2 | $ 37.8 | $ 4.47 | $ 2.39 | 10,415 | 8,800 |
| **Advanced Coal (IGCC)** | 0.85 | $ 4,400 | - | $ 37.8 | $ 7.22 | $ 2.39 | - | 8,700 |
| **Advanced Coal with seq** | 0.85 | $ 6,599 | - | $ 80.5 | $ 8.45 | $ 2.39 | - | 8,700 |
| **Combined Cycle(NG)** | 0.80 | $ 917 | $ 29.7 | $ 13.2 | $ 3.60 | $ 3.44 | 8,185 | 7,050 |
| **Advanced CC** | 0.87 | $ 1,023 | - | $ 15.4 | $ 3.27 | $ 3.44 | - | 6,430 |
| **CC with seq** | 0.87 | $ 2,095 | - | $ 31.8 | $ 6.78 | $ 3.44 | - | 7,525 |
| **Combustion Turbine** | 0.90 | $ 973 | $ 6.7 | $ 7.3 | $ 15.45 | $23.79/ $3.44 | 10.984 | 10,850 |
| **Advanced CT** | 0.90 | $ 676 | - | $ 7.1 | $ 10.37 | $ 3.44 | - | 10,850 |
| **Nuclear** | 0.90 | $ 5,530 | $ 112.8 | $ 93.3 | $ 2.14 | - | - | - |
| **Geothermal** | 0.92 | $ 4,362 | $ 89.8 | $ 100.0 | - | - | - | - |
| **Biomass (BFB)** | 0.83 | $ 4,144 | $ 120.6 | $ 105.8 | $ 5.25 | $ 2.32 | 13,500 | 13,500 |
| **On-shore Wind** | 0.30 | $ 2,213 | $ 34.2 | $ 38.5 | - | - | - | - |
| **Off-shore Wind** | 0.37 | $ 6,230 | | $ 74.0 | - | - | - | - |
| **Solar PV** | 0.15 | $ 4,183 | $ 14.6 | $ 27.7 | - | - | - | - |
| **Solar Thermal** | 0.20 | $ 5,067 | | $ 67.2 | - | - | - | - |
| **Hydro** | 0.52 | $ 2,936 | $ 14.2 | $ 14.1 | - | - | - | - |

Source: Availability factors are based on NREL (2006). All cost assumptions are based on EIA's Annual Energy Outlook Report (EIA-AEO, 2014). Also see EIA (2013b) for average heat rate estimates.

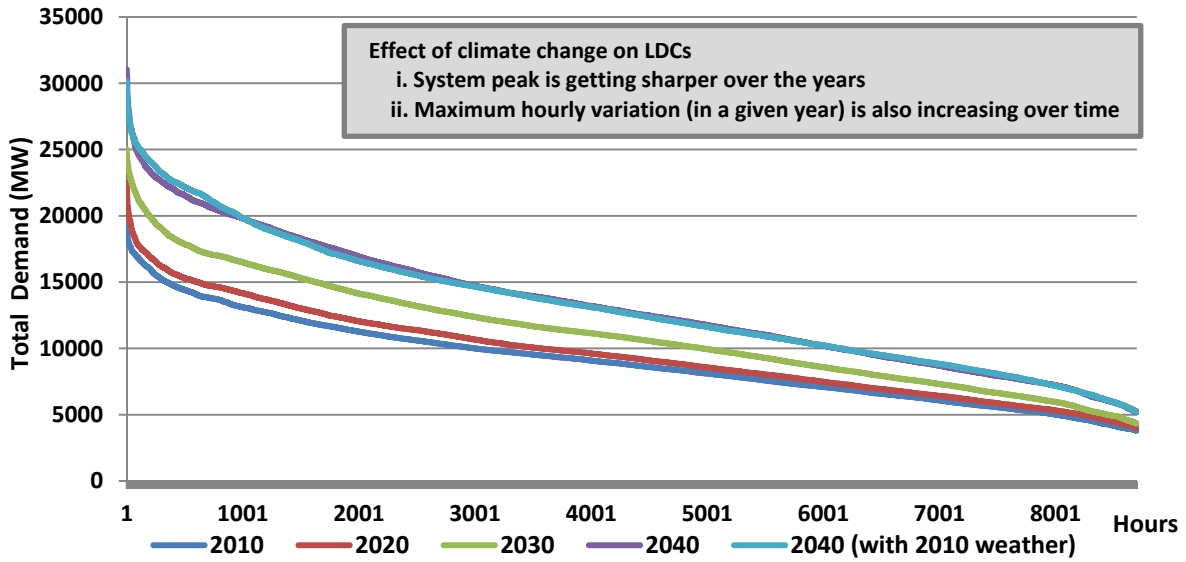
Notations: IGCC-Integrated Gasified Combined Cycle (IGCC); NG-Natural gas based combined cycles and steam turbines; seq- carbon sequestration system; BFB-Bubbling Fluidized Bed Boiler; CT- Combustion Turbine; PV-Photovoltaic

**Table 4.3: Existing generation portfolio (in MW) for the sub-regions in the Northeast region as of 2010**

| Capacity in MW | Coal | Combined Cycle & NG Steam Turbines | Combustion Turbine | Nuclear | Geothermal | Biomass | On-shore Wind | Solar PV | Hydro | Regional Total (MW) |
|---|---|---|---|---|---|---|---|---|---|---|
| **New England** | 2,855 | 17,648 | 2,244 | 4,654 | 5 | 830 | 277 | 5 | 3,477 | 31,995 |
| **New York State** | 2,683 | 9,064 | 1,242 | 3,182 | 5 | 205 | 1,273 | 23 | 5,554 | 23,231 |
| **New York City** | - | 10,599 | 4,755 | 2,037 | - | 240 | - | 20 | - | 17,651 |
| **New Jersey** | 2,036 | 10,243 | 1,395 | 4,060 | - | 276 | 8 | 28 | 410 | 18,456 |
| **Maryland- Delaware** | 5,940 | 3,440 | 3,955 | 1,705 | - | 12 | 72 | 2 | 590 | 15,716 |
| **Pennsylvania** | 18,481 | 9,415 | 4,633 | 9,540 | - | 525 | 700 | 10 | 2,268 | 45,572 |
| **Technology-wise Total (MW)** | 31,995 | 60,409 | 18,224 | 25,178 | 10 | 2,088 | 2,330 | 88 | 12,299 | 152,621 |

Source: EIA (2013 c); EIA-AEO (2014)

**Figure 4.4: Projected changes in Load Duration Curves (LDCs) for New Jersey**




Note: LDCs are used to study the trends in system demand over time. In the X-axis are hours in a typical year (*not* chronologically arranged).The Y-axis plots the system demand (MW) arranged in a descending order of magnitude.

The projected demand estimates for all sub-regions, except New Jersey, are based on AEO-2014 estimates (corresponding to the chosen economic growth scenario). The demand projection for New Jersey is based on Load Duration Curves (LDCs) plotted using temperature projections from CESM RCP 8.5 and economic projections (i.e. electricity demand by sectors) from R/ECON model runs. We use a Weather Response Function (WRF) of a utility based in New Jersey to track the changes in hourly system demand for a typical customer class (i.e. residential, commercial or industrial)[29]. These WRFs are regression equations linking surface temperature to electricity demand. In addition, these WRFs take into account the type of customer class, type of day (weekday or weekends) and type of hours (peak and off-peak). We then project these changes at a system level for each sector to see the overall trends in demand. Summing up

[29] Jersey Central Power and Lights (JCPL), January 2013. " JCPL Load Profile Application"- https://www.firstenergycorp.com/content/dam/supplierservices/files/loadprofile/Load%20Profile%20Application%20JC%20CLEAN_V2.pdf

the demand estimates for each sector we get the load profile curves for total demand (shown in Figure 4.4). The New Jersey LDCs are plotted for every ten years with demand estimates in the intervening years interpolated to match the trends.

The advantage of this approach, compared to merely assuming a constant growth rate, is that it also captures the changes in the shape of the load profile over the years. Figure 4.4 shows two key effects. The system peak is becoming sharper over the years and the maximum hourly variations in a given year is also increasing over the years. This shift could be attributable to factors such as economic and population growth, changes in sectoral composition of demand over the years and climate change effects. For New Jersey, the share of industrial and residential sector demand is set to decline in the coming decades. This decline corresponds to the increase in the share of commercial sector to the total demand. Under Reference scenario, the share of commercial demand increases from 51% in 2010 to 61% in 2040; the share of residential demand decreases from 38% in 2010 to 32% in 2040 and the share of industrial demand declines from 10% in 2010 to 6% in 2040. To illustrate the effects of climate change, the LDCs for the year 2040 is plotted using the NCAR-CESM projected weather and a baseline 2010 weather (as a hypothetical example).The difference in system peak demand is estimated to be 870 MW for the two pathways. The sharp increase in system peak demand is likely to result in the addition of peaking and intermediate units in the wider New Jersey region (i.e. mostly combined cycles and combustion turbines) under BAU assumptions. These hypothesized effects will be examined in the results from LP-CEM model runs. The peak demand estimates for other sub-regions in the Northeast were not readily available from the AEO-2014 report. Hence, the peak demand estimates are sourced from an Eastern Interconnection Power Consortium (EIPC) study on the future expansion of the Eastern Interconnection power grid (EIPC, 2013). The baseline projections from the EIPC study (2013) are used for the Reference scenario runs. For the High Growth theme, these peak demand projections are escalated to a higher rate (i.e. 10% more than

the Reference scenario escalation rate). Correspondingly for the Low growth theme, the peak demand projections are escalated at a lower rate (i.e. 10% less than the Reference scenario escalation rate).

On the supply-side, the LP-CEM models constraints on transmission and generation of power. Transmission networks between states/load zones are simplified to a "transport model" with limits on overall transfer capabilities. LP-CEM does not model transmission network expansion for the current set of model runs (some other GEMs like NREL's REEDS and SWITCH factor in transmission expansion as well; see Short et al., 2011; Fripp et al., 2012). The cost of transmission is fixed at $4 per MWh based on cost estimates furnished by system operator in the region for the year 2010[30] and assumed to increase at 1% every year. The transmission loss factor varies by season and year. The losses are acute in summer and in the later years when climate change effects are more pronounced. Transmission loss factors are based on the estimates found in the literature (see van Vilet et al., 2012; Sathaye et al., 2013; DOE, 2013; Chandramowli and Felder, 2014b). The planning reserve margin for each sub-region ranges from 15-16.5 % based on available data from system operators (summarized and presented in EIPC, 2013). Planned capacity retirements are based on EIA estimates used in AEO-2014 report. Construction limits for generating technologies are based on technological feasibility (for new technologies with carbon sequestration) and resource potential (i.e. for renewables like solar, hydro, wind and biomass).

The supply-side constraints are modeled by generation outage factors. This outage factor constrains the potential MWh of electricity that could be generated from a given generating technology. The generation outage factor is more pronounced in the summer months when the ambient temperature increase and cooling water availability is constrained. This generation outage factor is in addition to the capacity factor for each generating technology. Since the effect of climate change on renewable energy potential is

[30] PJM, June 2013- "State of the Markets Report 2011"(p.9) - http://www.monitoringanalytics.com/reports/pjm_state_of_the_market/2010.shtml
New England ISO(NEISO)- "Electricity Cost White Paper" – http://www.iso-ne.com/pubs/whtpprs/elec_costs_wht_ppr.pdf

unclear in the literature, the output from renewable energy sources is not subject to any generation outage factor (see DOE, 2013 & Chandramowli and Felder, 2014b for a review on the current state of the impact literature).

### 4.2.5 Scenarios used in LP-CEM model runs

This chapter models a total of six scenarios to analyze the power sector impacts of climate change. The three major scenario themes considered are: Reference case, High growth case and Low growth case. Each scenario theme is compared with and without climate change effects on both the demand and supply-side thereby resulting in a total of *six* scenarios. The R/ECON projections captures the changes in real GDP, population, personal income growth and employment trends in New Jersey. Total electricity demand/sales for New Jersey are expected to grow by 1.58 ± 0.03% a year for the three scenario themes. Likewise the demand projections for other sub-regions are expected to vary depending on the choice of AEO-2014 scenario chosen. The scenarios used in this chapter are patterned based on the AEO-2014's Reference case, High Growth and Low Growth case scenarios. On the supply-side the potential generation and transmission is subject to additional outage factors in a scenario incorporating climate change effects. The transmission and distribution (T&D) loss for the whole of U.S in the year 2010 is estimated to be around 7% [31]. Since the bulk of these losses are expected to occur in the distribution lines, we have modeled the simple transmission network in our model with a uniform 2% loss. However, under a climate change effect of increased ambient temperature, the thermal limits of transmission lines are likely to be exceeded (Sathye et al., 2013). Hence the percentage losses are more pronounced in the summer, followed by spring and fall. These effects are reflected by an increased loss factor ranging from 2-5% in the later years under a climate change scenario. Likewise on the supply-side, a climate change-induced outage factor is introduced to account for the effects of climate change.

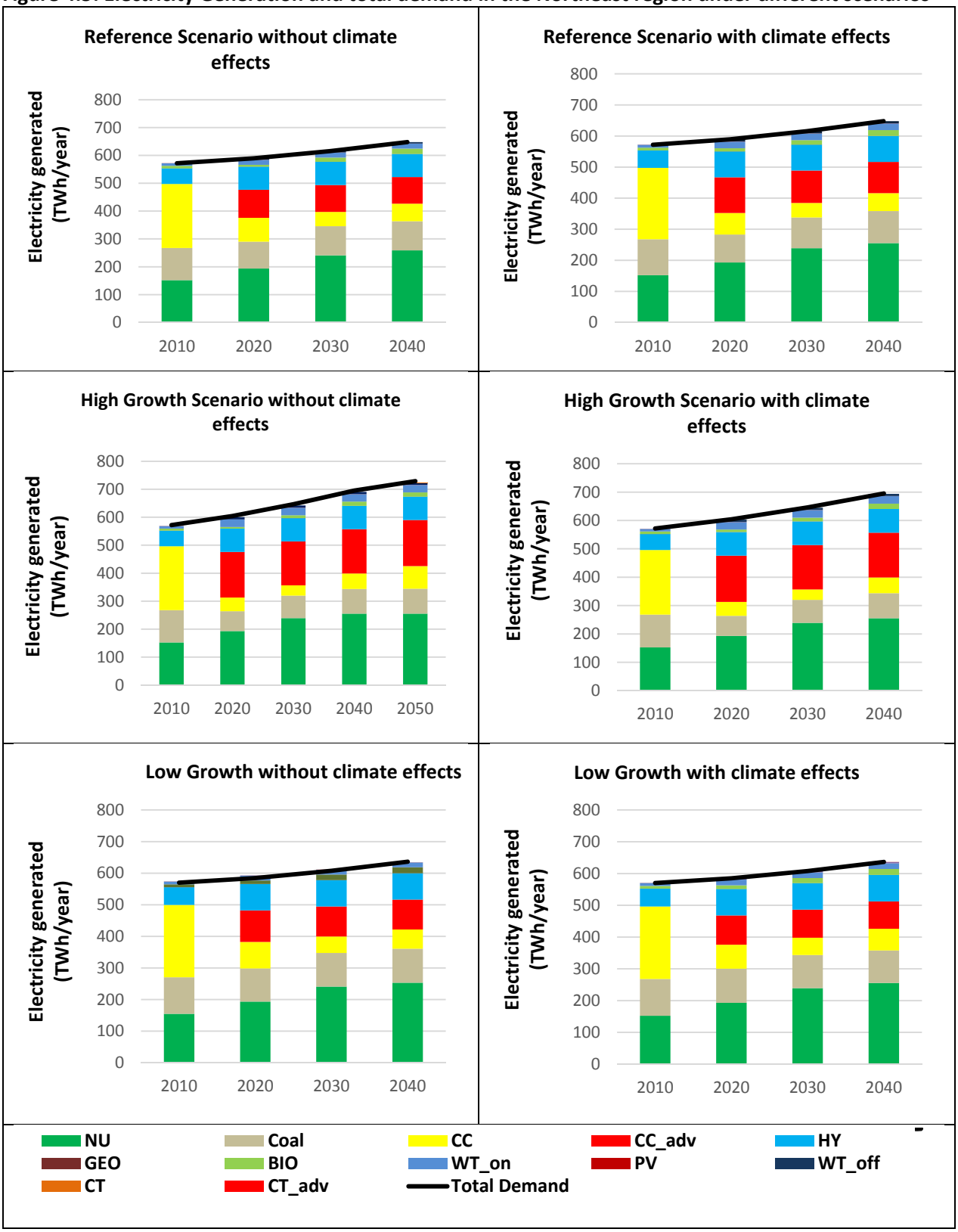
[31] US EIA- FAQs - http://www.eia.gov/tools/faqs/faq.cfm?id=105&t=3

Thermal power generation is constrained due to increased ambient air and cooling water temperature. This also reduces the efficiency of power generating units due to decreased temperature differential between the thermal source and sink. Various studies have estimated this decline to be 0.3-1% loss in MWh generated per °C increase in temperature depending on generating technology type, cooling systems and other climatic assumptions (Durmayaz and Sogut, 2006 ; Maulbetsch and DiFillippo, 2006; Linnerud et al., 2011; van Vliet et al., 2012; Sathye et al., 2013). Based on these estimates, we use an outage factor for -0.7% per °F increase for combined cycle units, -1% per °F increase for combustion turbine and -0.5% per °F increase for nuclear units. The outage factors are extrapolated from average temperature trends projected by the NCAR-CESM model run. The climate change outage is expected to be more severe in summer especially in the years beyond 2030. This outage factor is also reflective of the possible cooling water shortages or scarcity that is expected to occur in the distant future.

## 4.3 Results from LP-CEM simulation runs

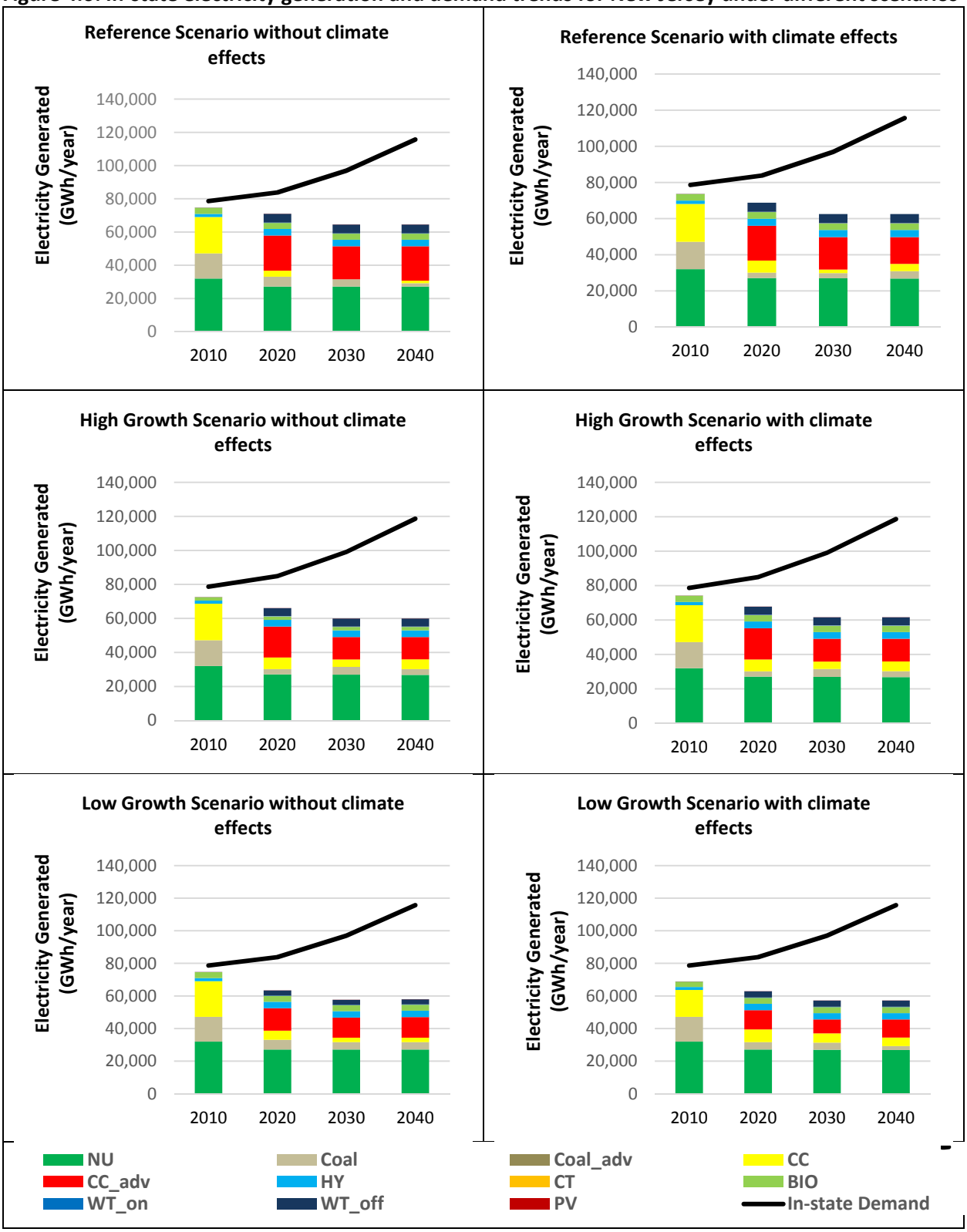
In this section we discuss some of the important outputs from the different model runs: electricity generation (GWh) trends for the Northeast region and New Jersey; type of capacity added (MW) to the region and wholesale/retail price ($/MWh) trends.

**Figure 4.5: Electricity Generation and total demand in the Northeast region under different scenarios**



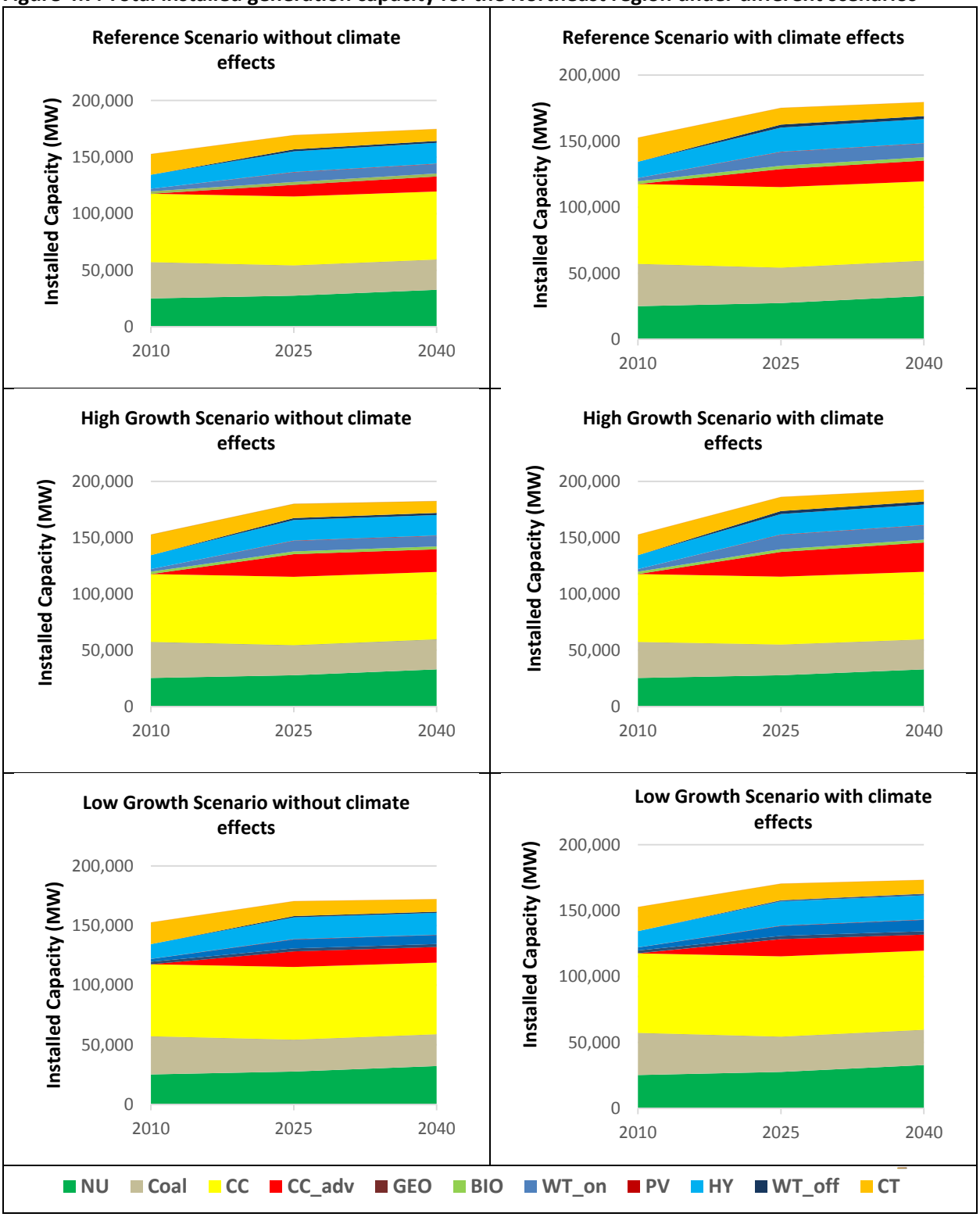

Note: The Northeast region includes the states in New England, New York, New Jersey, Pennsylvania, Maryland and Delaware.

**Figure 4.6: In-state electricity generation and demand trends for New Jersey under different scenarios**




Note: The in-state generation is not expected to correspond to the system demand in the state for all years. The excess generation denotes the GWh transmitted out of state to meet the demand in other load zones. Likewise, a higher system demand denotes the GWh imported from other load zones into the state.

**Figure 4.7: Total installed generation capacity for the Northeast region under different scenarios**




Note: Net capacity installation is represented as a gradual increase from 2010-2040 for illustration purposes only. The capacity increase occurs in sporadic batches at different intervening years in this period depending on demand projections and other scenario assumptions. Net capacity installation takes into account the planned retirement and additions of generation capacity. Un-planned retirements are ignored in the simulation runs.

**Figure 4.8: Capacity addition by technology type and sub-regions 2010-40 (for select scenarios alone)**

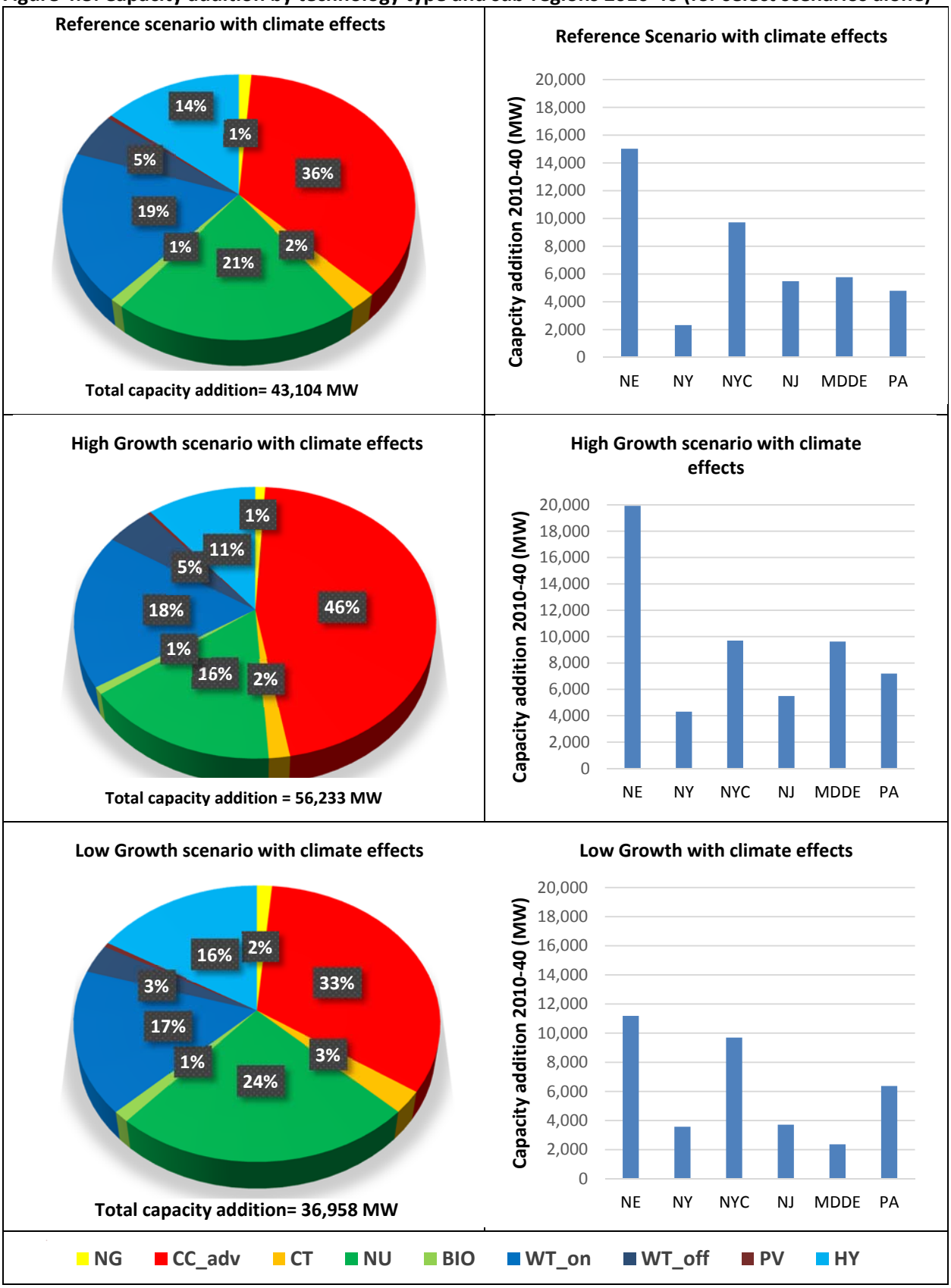
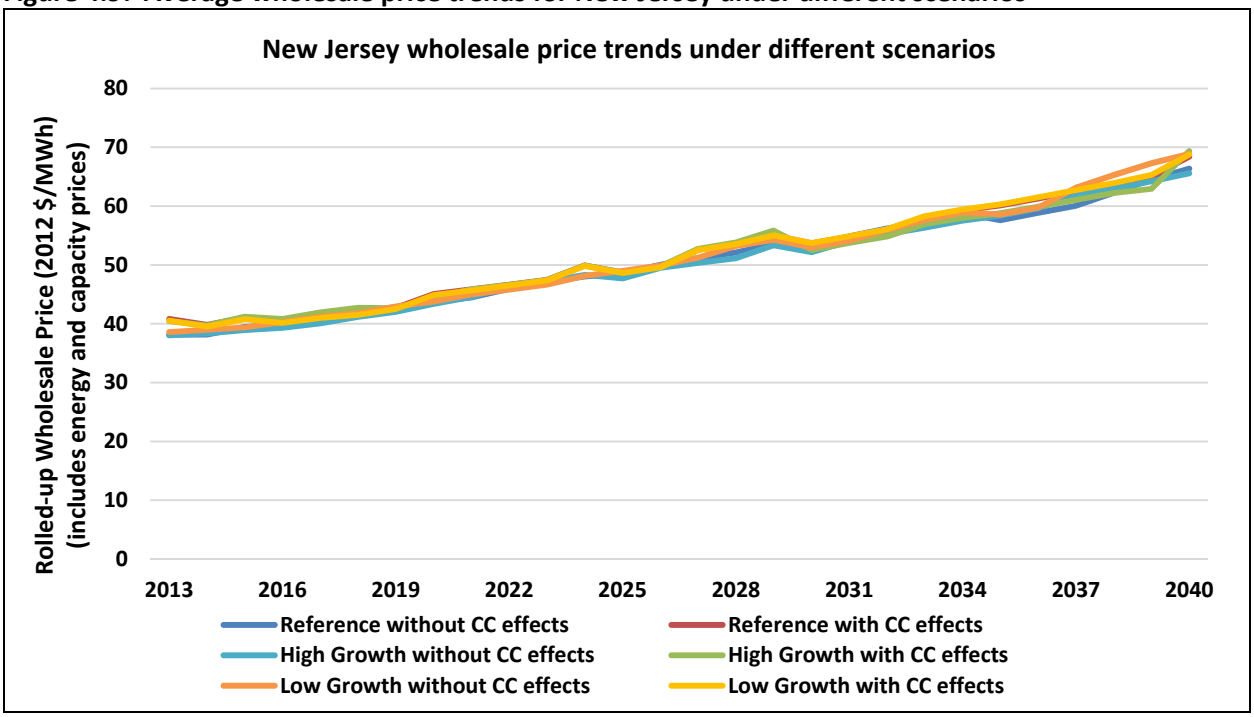
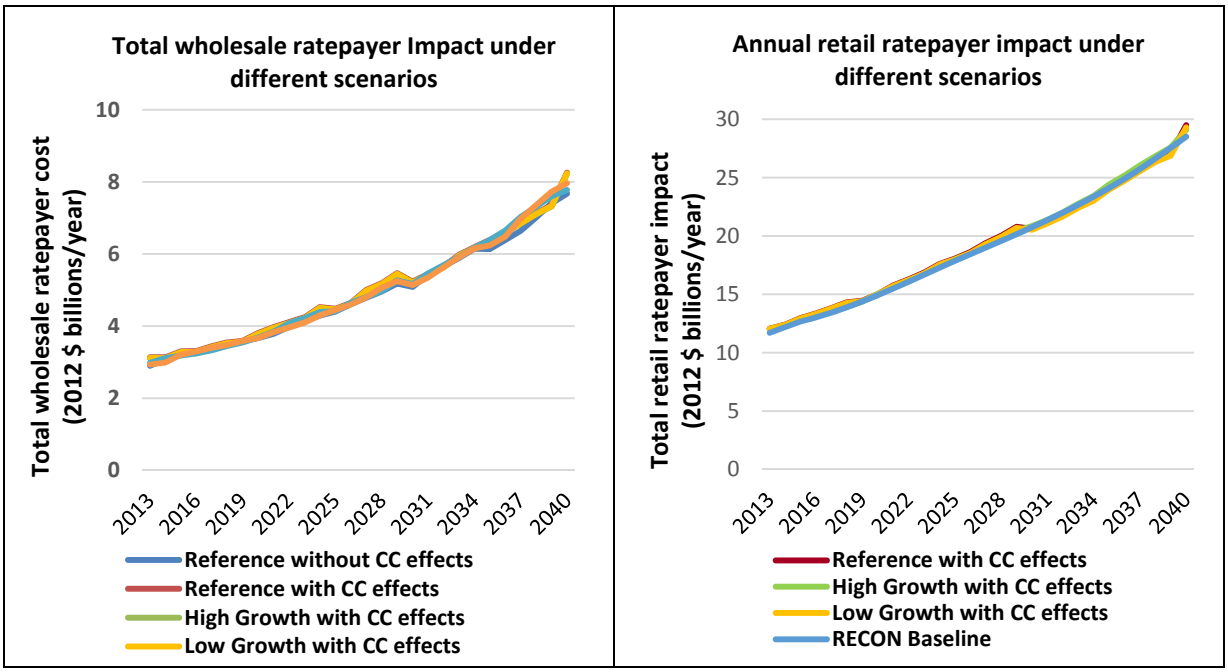


**Figure 4.9: Average wholesale price trends for New Jersey under different scenarios**



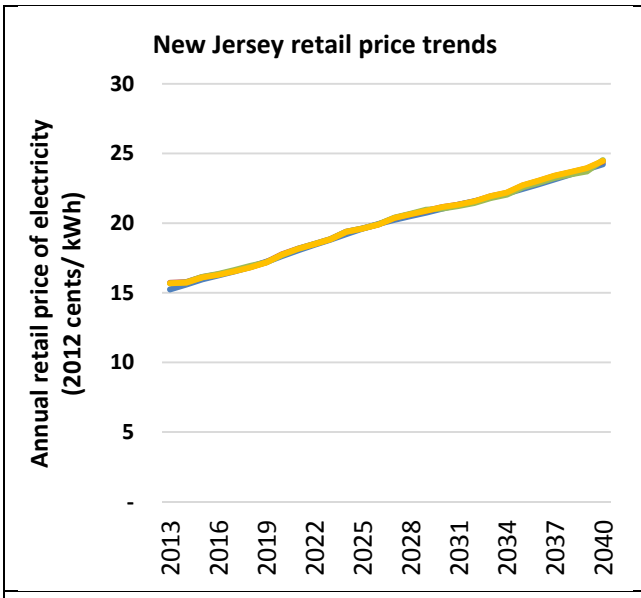

Note: Energy price is the dual variable of the energy constraint in the model (see Rau, 2003) for theory and formulation behind dual prices). This energy price is weighted by the seasonal demand to get the energy component of the annual wholesale price. The capacity price is based on the dual variable of the capacity constraint in the model. The whole of Northeast region is assigned a uniform capacity price ($/MW-year) for the intervening years based on the average dual capacity values for all sub-regions.

**Figure 4.10: Wholesale and retail ratepayer impact for New Jersey customers**




Note: The wholesale ratepayer impact is computed as the product of the rolled-up wholesale price and demand for a given year in New Jersey (and using annual retail prices for retail ratepayer impact). Since the wholesale component of electricity is only around 40-50% of the final retail prices, the fluctuations are not apparent in the final ratepayer impact graphs.

**Figure 4.10: Retail price trends for New Jersey under different scenarios**




| Scenario | NJ retail prices growth rate (CAGR) (2013-2040) |
|---|---|
| Reference Scenario | 1.65% |
| High Growth Scenario | 1.67% |
| Low Growth Scenario | 1.66% |
| **Scenario** | **NJ wholesale prices growth rate (CAGR) (2013-2040)** |
| Reference Scenario | 1.93% |
| High Growth Scenario | 2.02% |
| Low Growth Scenario | 1.98% |

**R-ECON Baseline Estimates** **Reference Scenario (with CC effects)**
**High Growth Scenario (with CC effects)** **Low Growth Scenario (with CC effects)**

Note: Retail Prices are usually expressed in cents/kWh (i.e. 100 $/MWh is 10 cents/kWh). The retail price trends are based on the R/ECON Baseline input. The new set of retail prices, labeled as "coupled" prices, incorporates the premium of climate effects on the wholesale component of the retail price. The wholesale component is about 40-50% of the final retail price for New Jersey (CEEEP, 2011: pp. 10-19). We *do not* estimate the climate change effects on other components of the final retail price (like distribution, Federal & state taxes and regulation costs).
CAGR-Compound Average Growth Rate

**Figure 4.12: Differences in wholesale and retail ratepayer impact under different scenario themes**

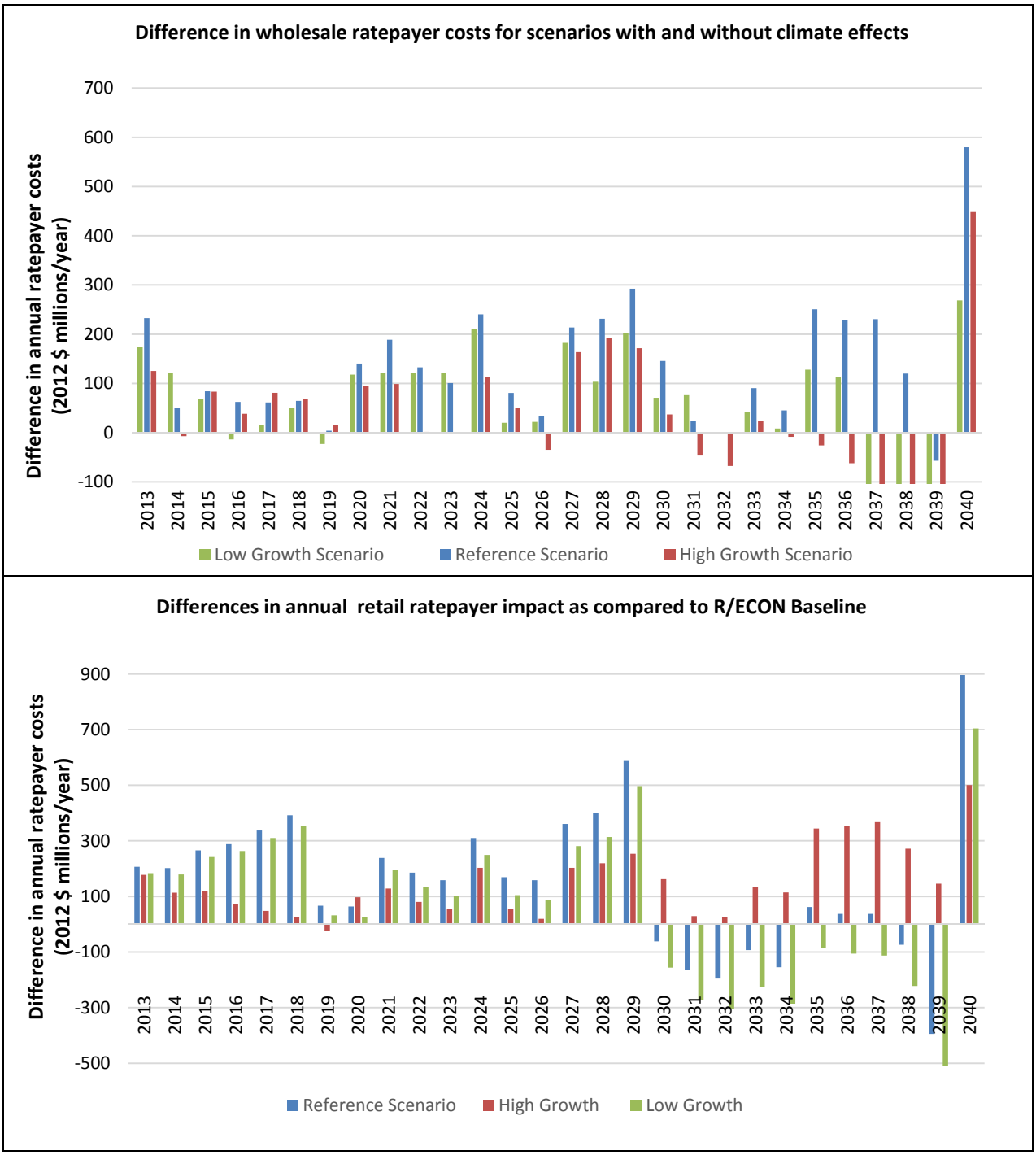
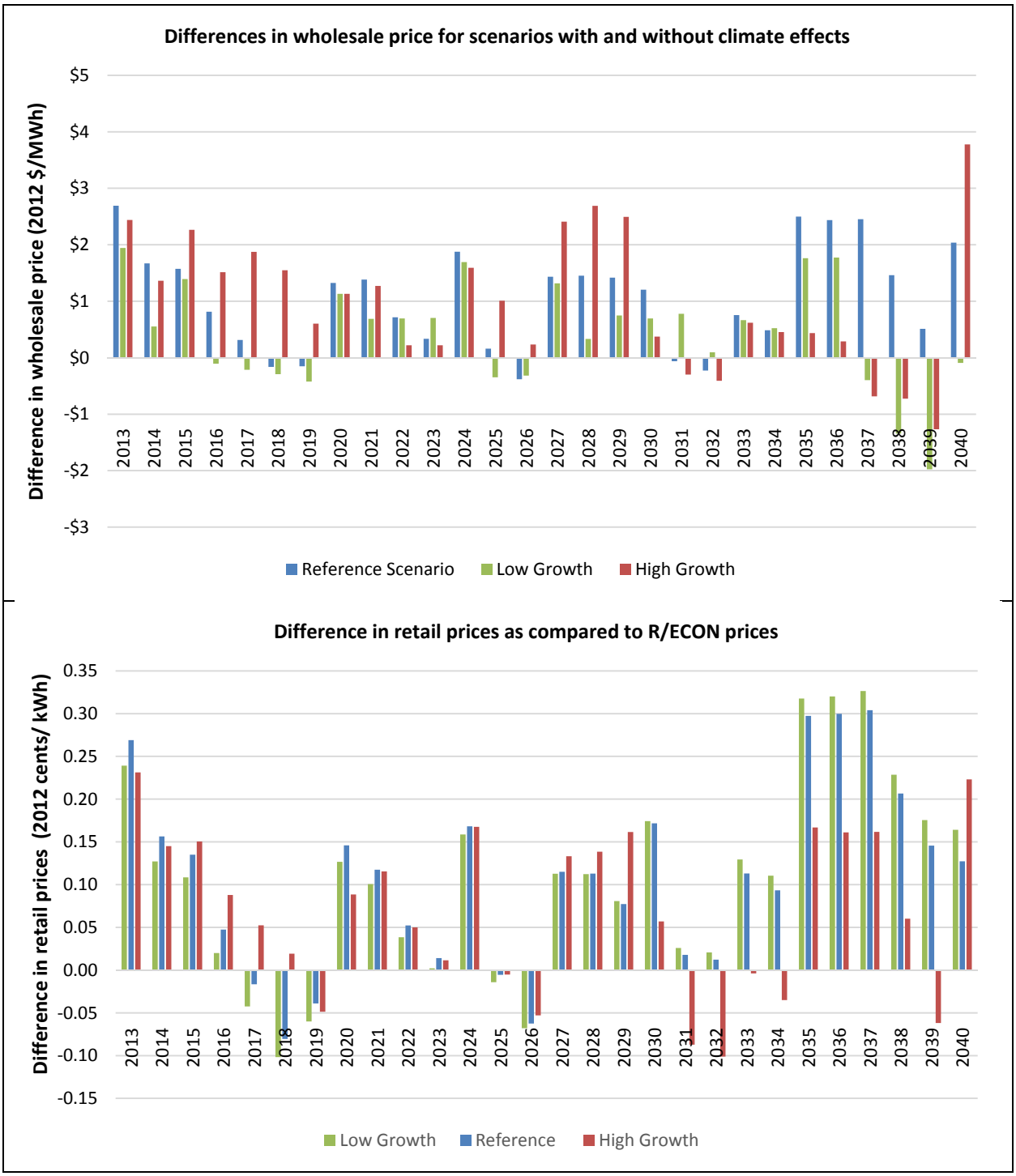


**Figure 4.13: Differences in wholesale and retail prices under different scenario themes**



Based on the electricity generation profiles for the Northeast region and New Jersey (Figures 4.5 and 4.6), *three* distinct trends are observable. First, the share of electricity generated from advanced combined cycle units is expected to increase substantially in the coming decades. This is likely to replace the share of electricity generated from conventional natural gas units. Overall the share of power generated from conventional natural gas based units is expected to decline from 40% in 2010 to about 26-27% in 2040 under different simulation runs. Secondly, the share of power generated from nuclear is expected to increase in the later period of the model simulation (i.e. beyond 2025). The share of nuclear generation is expected to increase from 26% in 2010 to about 35-39% by 2040 under the various scenario themes for the Northeast region. This is because new nuclear capacity addition in the model is subject to a mandatory fifteen year waiting period to account for regulatory approval and average construction time. Also, the model takes into account only the planned retirements as available in the AEO-2014 report. Many of the nuclear plants built in the 1960s-1980s are licensed to run for a period of 60 years[32]. There is a possibility that some of the nuclear plants in the Northeast could be decommissioned in the coming decades due to licensing regulations and non-viable power generation costs. Hence, the projected share of the nuclear generation is likely to be overestimated in the model runs. Thirdly, the share of renewables is also expected to grow in the coming decades. Overall, the share of generation from renewables, including hydro, is expected to increase from 12-13% in 2010 to 19-20% in 2040.

The existing Renewable Portfolio Standards (RPS) requirements are modeled as a percentage of total generation in a year (around 20-25% for each sub-region by the year 2025 and remaining constant for the rest of the simulation period)[33]. Also, the share of hydro-generation (including pumped storage) in the

[32] In the US, commercial reactors are granted a 40-year initial operating license. This can be extended for another 20 years depending on plant conditions and safety regulations. See: http://www.nrc.gov/reading-rm/doc-collections/fact-sheets/fs-reactor-license-renewal.html

[33] RPS requirements are derived from the Database of State Incentive for Renewable Energy and Energy Efficiency (DSIRE) (US Department of Energy-North Carolina Solar Center)- http://www.dsireusa.org/rpsdata/index.cfm

Northeast is expected to increase modestly in the later years. This is partly due to the fact that hydro-units are factored in as a renewable source for modeling purposes. Even in the absence of any major emissions policy assumptions (i.e. in the current set of model runs), the share of coal generation shows a moderate decline in the coming decades. This partly reflects the non-viable cost economics of generation from coal-based units (see Schlissel, 2013). Power generated from on-shore wind, off-shore wind and biomass is expected to contribute significantly to meet the RPS requirements in the future. Generation from other sources like grid-interactive solar PV and biomass are too small to be discerned clearly in the charts. These three key trends are also visible in the case of New Jersey's generation profile (see Figure 4.5). For New Jersey, the share of in-state generation is poised to decline substantially in the coming decades. By 2040, nearly half of New Jersey's total demand is expected to be met by out-of-state generation resources.

Figure 4.7 plots the generation capacity mix for the Northeast region under different scenarios. This takes into account planned retirements and capacity additions (both planned and unplanned). The total installed capacity in the Northeast is likely to increase from 152, 000 MW in 2010 to about 172,000 MW - 195,000 MW in 2040 under different scenario assumptions. Generally scenarios with climate change and variability effects have a higher capacity additions to account for generation and transmission constraints. Figure 4.8 plots the capacity additions by technology type for the whole of Northeast region and by individual sub-regions. For scenarios without climate change effects, the capacity addition is 36,700 MW for Low Growth theme; 38,400 MW for Reference theme and 46,000 MW for High Growth theme. For scenarios with climate change and variability effects, the capacity addition is 36,900 MW for Low Growth theme; 43,100 MW for Reference scenario theme and 56,200 MW for High Growth theme. The bulk of capacity addition is expected to occur in advanced combined cycle units; nuclear and on-shore wind (see pie-chart in Figure 4.8). The installed capacity share of natural gas based technologies is not expected to vary much from 2010 to 2040. The share of renewables is expected to increase from 11% in 2010 to 17-

18% in 2040 under different scenario themes. Also, the current set of model runs fails to account for unplanned retirements in existing combined cycles and other conventional units. Hence the total installed capacity estimate is likely to be over-estimated in the current simulation runs.

Had long-term retirements been factored in the model runs, the quantity of new capacity addition would likely be higher. In the model, retirement decisions of power plants are strictly based on cost economics of power production and regulatory environment of electricity wholesale markets. The Northeast region is characterized by competitive wholesale markets wherein the dispatch of power from individual power plants are based on price bids and market clearing price. Under these circumstances, it is difficult to ascertain the long term plans of individual generation units based on average costs of generation alone. Hence, the model assumes only the planned capacity retirements by load zones/sub-regions which are usually accurate for the near term period[34].

Finally, we can also project the trends in wholesale and retail prices of electricity under different scenarios from the LP-CEM model runs[35]. The dual variable of the energy and capacity constraint of the model yields the energy and capacity component of the wholesale electricity prices (see Rau, 2003) for theory and formulation behind dual variables). Figure 4.9 highlights the trends in average wholesale prices over the simulation period. Figure 4.11 projects the retail price trends for the same period. Naturally, the difference in prices is higher under a High Growth scenario theme. Similarly, differences are also higher in the later years due to higher system demand levels and a more pronounced climate change constraint on the supply-side. This results in a high wholesale price deviations for scenarios with and without climate change

[34] For current planned capacity retirement see: http://www.eia.gov/todayinenergy/detail.cfm?id=7290. Also, refer to the latest *EIA Form 860- Annual Electric Generator Report* for an up-to date list of plant retirements.

[35] In the LP-CEM context, the wholesale price of electricity includes energy and capacity price components. It reflects the price at which generators are compensated. The retail price represents the final price paid by the end consumer. It includes the wholesale price, transmission and distribution costs, regulation costs for policy programs (like RPS and emissions cap), and Federal/state taxes.

effects. A High Growth scenario incorporating climate change (CC) effects has the highest deviation from a reference scenario projection. For the years 2013-40, the average annual load-weighted wholesale prices are: $51.40 $/MWh for a low growth scenario with CC effects; $ 52.12 $/MWh for Reference scenario with CC effects and $ 53.11 $/MWh for High Growth scenario with CC effects (all prices are in 2012 $). The corresponding average price for Reference scenario without climate change is around $ 50.46 $/MWh.

Figure 4.10 plots the corresponding wholesale ratepayer impact for New Jersey customers. The wholesale ratepayers' impact is computed as the sum of the payment made to the energy component and the capacity component of the wholesale electricity prices. As expected, the High Growth scenario with CC effects has the highest wholesale ratepayers' impact. All three climate change scenarios have a higher wholesale ratepayer impact on customers in New Jersey. The fluctuations in wholesale price impact are ironed out in the final retail ratepayer impact for New Jersey customers. This is because the wholesale component of the price is only 40-50% of the final retail price for New Jersey customers (CEEEP, 2011). The High growth scenario with climate change effects has consistently high ratepayer impact throughout the simulation period. A low growth scenario has correspondingly the lowest impact for the end consumers. The difference in the wholesale and retail ratepayer impacts after the LPCEM-R/ECON coupling run is plotted in Figure 4.12. For the years 2013-40, the cumulative difference in wholesale ratepayers' impact due to CC effects is estimated to range from $ 884 million to $3,868 million (all terms in 2012 $). Cumulatively, the difference in retail ratepayers' costs is expected to range from $1.91 to $4.29 billion under different scenario themes (all terms in NPV $). Figure 4.13 plots the difference in wholesale and retail prices due to CC effects. For the years 2013-40, the average annual increase in final retail price is expected to range from 0.07 to 0.11 cents/kWh (2012 $). This increase is with reference to R/ECON baseline projection and also factors in the elasticity of demand to projected price increase (i.e. after R/ECON-LPCEM coupling).

## 4.4 Summary – Key LP-CEM results and insights

This chapter demonstrates the feasibility of incorporating climate change effects and macroeconomic trends into a GEM/CEM framework. For New Jersey's case, this is accomplished by coupling the LP-CEM model to R/ECON macroeconomic model. Such integrated models can be of use to state/regional level policymakers to plan for future mitigation and adaptation measures and to assess the impacts of various policy interventions on energy investments and macroeconomic outcomes. The LP-CEM model also provides a framework to project the societal costs of possible clean energy policies. The different scenarios outlined in this chapter will all have important economic implications for the state. Some of the key insights from the current set of model runs are summarized below:

- Scenarios with climate variability, climate change effects and high economic growth rates have consistently resulted in *higher* capacity additions (in MW), supply costs, prices and ratepayers' costs.
- From the LDC modeling effort and LPCEM simulations, the bulk of the capacity addition is expected to be advanced combined cycle units for the Northeast region. These units can supply to both intermediate and peak system demand. Nuclear and on-shore wind additions are also likely to be substantial in the coming decades for the Northeast region (based on cost-economics considerations alone).
- Interestingly, the compound average growth rate (CAGR) for wholesale price projections, under all scenario themes, corresponds closely to the fuel cost escalation rate for natural gas (at 2.1% a year). This is because natural gas units are expected to set the marginal wholesale price at most
- For the years 2013-2040, the average annual increase in final retail price for New Jersey is expected to be around 0.08-0.11 cents/kWh (2012) assuming the climate change and variability effects on the wholesale price component *alone*. The final effect on the retail prices are most

likely to be higher if the effects of climate change on dispatch, distribution, ancillary services, regulatory costs, and grid reliability are also factored in.

- For the years 2013-2040, the cumulative increase in wholesale ratepayers' impact due to climate change and variability effects is estimated to range from $ 0.8 billion to $3.8 billion (all terms in NPV $) under different scenario themes. This represents the increase in wholesale cost of electricity for ratepayers in New Jersey due to long-term climate change effects alone. This increase is computed with reference to the corresponding scenario theme without climate change effects.
- For the years 2013-2040, the cumulative increase in retail ratepayers' costs is expected to range from $1.9 to $4.3 billion under different scenario themes (all terms in NPV $). This increased energy cost is likely to have ripple effects on the wider macro-economy of New Jersey. This ratepayer cost increase is computed with reference to a baseline R/ECON projection.

The economic- electricity model "coupling" used in this research has the additional advantage of analyzing the broader price impacts on the macro-economy. This research has also demonstrated the coupling framework by feeding the retail price outputs from LP-CEM back into the R/ECON model to calculate the new set of regional demand and other key macroeconomic projections. This "coupling loop" could be continued until a convergence is achieved in key economic-energy sector parameters. In addition, the current version of the LP-CEM optimization model operates on a deterministic framework which assumes perfect foresight over a future planning horizon. Climate change impacts, on the other hand, are usually characterized by high degree of uncertainty. In the future, we are hoping to integrate this climate change uncertainty by relying on an ensemble of "downscaled" GCM projections; incorporating the parametric distribution of climate change variables (like climate change outage rates and transmission loss factors) and running multiple simulation runs of the model to arrive at the expected cost estimates. Finally, the modeling approach used in this study did not consider the impact of extreme weather events. These

events have the potential to inflict enormous costs on the society and cause widespread damage to power systems assets (also see discussions in Chapter 6 on Hurricane Sandy and its impact on the sector). Infrastructural adaptation measures to extreme events are a key component of climate change response strategy. This remains an important topic for future research work.

# Chapter 5

# Evaluating the policy interaction effect of renewable portfolio standards (RPS) and carbon cap scenarios for the U.S Northeast

This chapter applies an analytical model and an optimization model to investigate the implications of co-implementing an emission cap and an RPS policy for the U.S Northeast. A simplified analytical model is specified and the first order optimality conditions are derived. The results from the analytical model are corroborated by running LP-CEM simulations under different carbon cap and RPS policy assumptions. The marginal abatement cost estimates, derived from a set of LP-CEM model runs, are analyzed and compared to the theoretical result using a stylized example. From a strict supply cost optimization perspective, the proposed Clean Power Plan (i.e. EPA's 111(d) rules) is likely to result in a moderate increase in ratepayers' cost in the next forty years. A combination of RPS and emissions cap policies is likely to have a beneficial effect for the ratepayers in this region.

## 5.1 Introduction

Emissions cap and renewables portfolio standards (RPS) are two commonly used policy instruments to address the problem of GHG emissions from the electric power sector. These instruments are designed to mitigate the negative environmental externalities associated with major power sector pollutants like carbon dioxide ($CO_2$), sulfur dioxide ($SO_2$) and oxides of nitrogen (NOx). Under a cap-and-trade type trading approach, an overall cap is set on the total emissions of a pollutant in a given year and individual generators are mandated to have adequate allowances equal to or exceeding their emission output. On the other hand, renewable portfolio standards (RPS) are policy instruments designed to encourage the adoption of clean and renewable energy technologies. RPS requires the load serving entity in a region to procure a certain fraction of the electricity generated from qualified renewable resources. An associated market for renewable energy certificates (REC) creates an additional revenue stream for qualified generators and serves as a means for load serving entities to fulfill the mandated renewables target. When these two policy instruments are co-implemented, the precise nature of the interaction effect is not known due to conflicting findings in the literature (del Rio, 2007). The interaction effect of these two policy instruments could lead to synergies or conflicts in overall societal costs and benefits. Also, the effect of

policy interaction on wholesale prices and ratepayers' cost is also not clear from the literature. Although these policies are motivated by the underlying environmental benefits, there are other co-benefits like economic development, creation of skilled jobs, fostering technological innovation and resource diversity (Jensen and Skytte, 2003; Gonzalez, 2007).

This chapter applies an analytical model and an optimization model to simulate the implications of the policy interaction effect for the U.S Northeast. The analytical model is outlined in Section 5.3 of this chapter. The market equilibrium (defined using MWh of generation and MW installed capacity of each technology as the key decision variables) is calculated using the first-order optimality conditions for the analytical model. Given the market equilibrium conditions, the chapter compares the marginal cost metrics associated with an emissions cap and an RPS constraint. These marginal cost metrics reflect the marginal abatement cost associated with each policy instrument. The results from the analytical model are corroborated by running simulations using LP-CEM, a supply cost optimization model for the U.S Northeast region. The marginal abatement cost metrics from a limited set of LP-CEM model runs are analyzed and compared to the theoretical results derived from the analytical model. This chapter also presents the implications of the EPA's proposed Clean Power Plan rules (EPA-RIA, 2014) on the overall societal costs and electricity prices for the Northeast region (in Section 5.5). The results from the generalized analytical model and LP-CEM simulation runs for the Northeast region are summarized in the final section (Section 5.6).

The policy interaction effect has been documented in a number of qualitative case studies and has also been analyzed using quantitative modeling simulations (see Gonzalez, 2007 for an overview of the literature). One of the earliest research studies on this policy interaction effect is that of Jensen and Skytte (2002). The study uses a deterministic-equilibrium model to investigate the effect of RPS obligations on electricity prices (in a simplified version of the spot market). The study concludes that the effect of RPS on electricity prices is ambiguous. This is due to the fact that increasing RPS mandates could result in a

price suppression due to displacement of high variable cost fossil fuel generation by a low or near zero variable cost renewable energy generation (see Felder, 2011 for a theoretical overview of price suppression effect). However, this could also increase the price support and demand for RECs, thereby increasing the final price. In a related study, Jensen and Skytte (2003) analytically show that the effect of RPS-type policies and emission caps is not an unambiguous increase in wholesale/retail prices. Instead, the final price effect depends on the relative proportion of renewables and emissions cap. Palmer and Burtraw (2005) concludes that an RPS policy is superior to an emissions cap in encouraging renewable energy deployment in the U.S. Correspondingly for emissions reduction goals, a cap-and-trade program is shown to be cost-effective. Gonzalez (2007) analytically shows that a co-implementation of an RPS program and an emissions trading scheme could result in synergistic advantage, provided there is coordination in the respective program targets. Linares et al. (2008) analyze the interaction effect of emission trading and RPS for the Spanish electricity market using a complementarity optimization model. They conclude that coexisting policies increase the final retail/wholesale due to renewable and emission credit price components. Tsao et al. (2011) use an analytical and a computational modeling approach to analyze the short-run market implications of policy interaction effects. They conclude that making any one policy more stringent would weaken the market incentives for the other, thereby rendering the other policy redundant. Bird et al. (2011) uses a generation expansion model to study the generation mix, price trends and carbon emissions under different combinations of emissions cap and RPS targets. They conclude that a combination of RPS and emissions cap does not lead to a substantial increase in electricity prices, reduces $CO_2$ allowance price, and results in greater renewable capacity addition in the near term. Based on this limited review of the literature, one can draw three broad conclusions. First, the respective policy goals are best achieved cost-effectively using the appropriate instrument (i.e. deployment of renewable technologies is best achieved using an RPS instrument and emissions reduction is best achieved using an emissions cap). Second, there could be some synergistic advantage in implementing the two

policies together but it depends on the relative differences in emissions and renewables targets. Third, the impact of policy interaction effect on final retail/wholesale prices and costs is ambiguous and appears to depend on the context and settings (geographic regions and market designs).

## 5.2 Examples of co-implementation of an emissions cap with RPS in the United States

There has been limited experience in implementing an emissions cap program with an RPS (also see Bird et al., 2011). In the U.S., there are currently only two programs with a mandatory emissions cap for $CO_2$ emission and an RPS program[36]. The two mandatory emissions cap programs are the Regional Greenhouse Gas Initiative (RGGI) for Northeastern states and California's cap-and-trade program. California's program was launched in January 1, 2013. The program aims to return to 1990 level of GHG emissions for the state by the year 2020 (CA ARB, 2014; EDF, 2014). The cap is set to decline by 2% for the first two years (2013-2014) and 3% every year from 2015-2020 (as compared to a business-as-usual (BAU) estimate). A review after the first year showed a robust market for allowances and a high degree of compliance with the cap (EDF, 2014).

RGGI started with the Northeastern states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont forming a consortium to control $CO_2$ emissions from power plants in the region. New Jersey has since left RGGI in 2012 leaving the consortium with nine member states. RGGI's cap came into effect in 2009 and requires a 10% reduction in $CO_2$ emissions from participating states by 2014 (RGGI, 2014). The original cap calls for setting the total power sector emissions in 2014 at 91 million short tons of $CO_2$ (ibid.). The cap is set to decline by 2.5% every year till 2020. After New Jersey's departure, the cap was adjusted accordingly to reflect the emissions from the remaining nine member states. Also, the region's largest $CO_2$ emitter, Pennsylvania, is not a member state

[36] There are Federal cap-and-trade programs for other pollutants like sulfur dioxide ($SO_2$) and oxides of nitrogen (NOx) from thermal power plants. The discussions in this chapter are confined to $CO_2$ cap alone. Also see http://www.epa.gov/captrade/

of RGGI either[37]. The RGGI cap is relatively modest in its requirements for the initial years till 2014 and as a result the price of allowances has remained low in the range of $2-3 per short ton of $CO_2$ (Bird et al., 2011). The revenue from the sale of $CO_2$ allowances is designed to support energy efficiency and renewable energy programs. The $CO_2$ allowance market under RGGI is *not* coupled to the state-level renewables credits market[38]. Renewable energy generators are not directly affected by RGGI rules and consequently they do not participate in the $CO_2$ allowance market. Also, the extent to which renewable energy has been promoted in member states using the revenues from $CO_2$ allowances has not been systematically analyzed in the literature so far. Hence the market framework in the Northeast region is characterized by two distinct policy instruments with each tailored to a specific objective.

In June of 2014, the Environmental Protection Agency (EPA) issued a set of proposed emissions rules for existing thermal power plants under the provisions of the Clean Air Act (CAA) Section 111(d)[39]. These proposed rules are informally called the Clean Power Plan. All existing fossil fuel-fired power plants in the country (25 MW rated capacity and above) are affected by this proposed rule. The proposal calls for states to implement an emission reduction plan through the application of the "best system of emission reduction" (BSER). The rule envisions emissions reduction in carbon dioxide through the following four "building blocks" (EPA-RIA, 2014):

- reducing the carbon intensity of generation at individual plants through efficiency improvements

[37] See: http://www.epa.gov/reg3artd/globclimate/ccghg.html

[38] The implications of coupling of a market for emissions allowances and the one for renewable credits are explained in Sorrel et al. (2003). The study reports three types of coupling between the two markets: full fungibility, one-way fungibility and a complete separation. In a full fungibility arrangement, emissions reductions caused by a unit of renewable generation would be tradable in an emissions cap market (*vice versa* for renewable markets). A one-way fungibility denotes an arrangement that is valid for one market alone. These two types of market arrangements are not common due to complexities in ensuring credit equivalence, increased transaction costs and failure to consider other local benefits of RPS.

[39] "Carbon Pollution Emission Guidelines for Existing Stationary Sources: Electric Utility Generating Units"- A Proposed Rule from US E.P.A (40 C.F.R 60) (2014)**- https://federalregister.gov/a/2014-13726**

- substituting power generation from carbon-intensive source with less carbon-intensive source (a switch from coal to natural gas)
- substituting power generation from carbon-intensive source with zero-carbon sources like renewables and nuclear
- reducing emissions from the power sector using energy efficiency and demand-side management

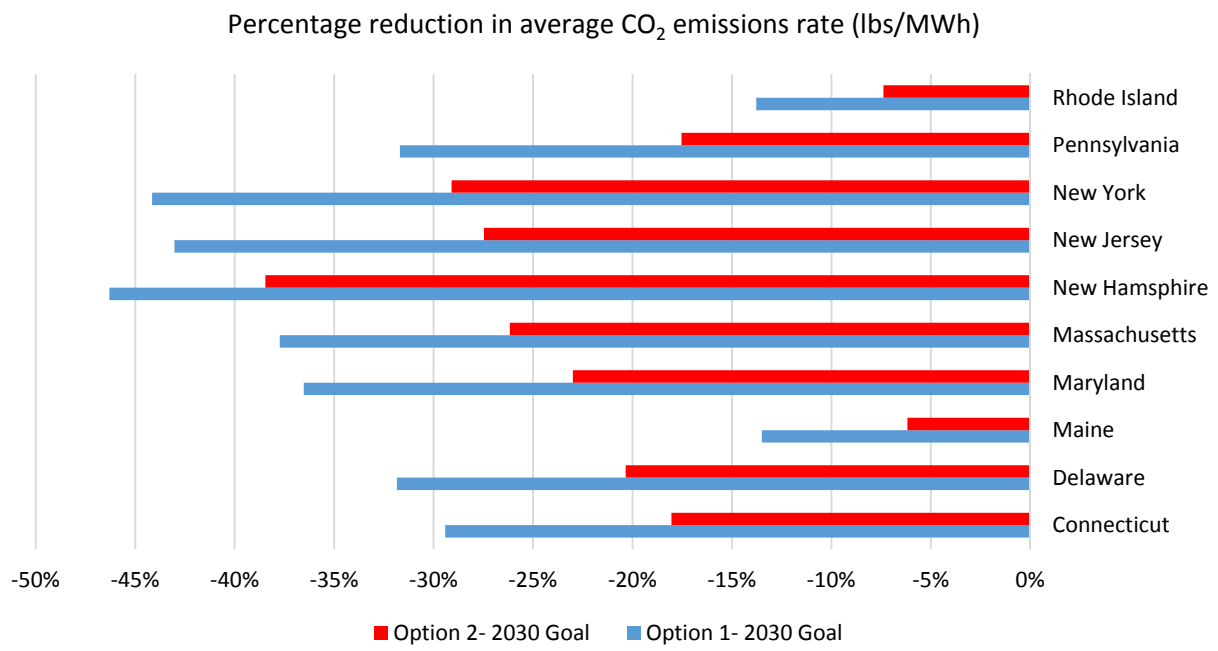
The proposed rules have also fixed state-wide emissions rate goals to provide a benchmark for emissions reductions (see Table 5.1). The proposal allows individual states to design their own plan using one or a combination of these four "building blocks". The states are given the flexibility to collaborate with other states in ensuring compliance to the emission standards on a regional or a multi-state basis. The EPA has identified two approaches to emissions reductions. *Option 1* involves a higher reduction in $CO_2$ emissions but a longer timeframe to comply (till 2030) whereas *Option 2* has a lower reduction target for $CO_2$ emission with a shorter timeframe (till 2025). The state-wide average emission rates for Northeastern states are listed in Table 5.1. Although states have the flexibility to design their own compliance approach, it is likely that the Northeastern states would prefer a market-based cap-and-trade approach for compliance with the Clean Power Plan mandates (Pew Center, 2011; C2ES, 2014). The model runs in this chapter are based on the assumption that all Northeastern states would join a cap-and-trade program with a binding regional emissions cap commensurate with the state-wide emissions rate goals. Figure 5.1 represents the percentage reduction in the $CO_2$ emissions rate for Northeastern states under Clean Power Plan in 2030.

**Table 5.1: Proposed state $CO_2$ emissions rate goals (weighted average lbs/MWh)**

| State | | *Option 1 (lbs/MWh)* | | *Option 2 (lbs/MWh)* | |
|---|---|---|---|---|---|
| | 2012 Average emissions rate (lbs/MWh) | Interim Goal (2020 - 2029 average) | Final Goal (2030 and thereafter) | Interim Goal (2020 - 2024 average) | Final Goal (2025 and thereafter) |
| Connecticut | 765 | 597 | 540 | 651 | 627 |
| Delaware | 1234 | 913 | 841 | 1,007 | 983 |
| Maine | 437 | 393 | 378 | 418 | 410 |
| Maryland | 1870 | 1,347 | 1,187 | 1,518 | 1,440 |
| Massachusetts | 925 | 655 | 576 | 715 | 683 |
| New Hampshire | 905 | 546 | 486 | 598 | 557 |
| New Jersey | 932 | 647 | 531 | 722 | 676 |
| New York | 983 | 635 | 549 | 736 | 697 |
| Pennsylvania | 1540 | 1,179 | 1,052 | 1,316 | 1,270 |
| Rhode Island | 907 | 822 | 782 | 855 | 840 |

Note: Vermont has no fossil fuel units and consequently is not affected by the proposed rules.
Source: EPA-RIA, 2014.

**Figure 5.1: Percentage reduction in $CO_2$ emissions rate for Northeastern states under Clean Power Plan**




Source: EPA-RIA, 2014.

## 5.3 A mathematical framework for modeling an emissions cap with RPS

In this section, the first-order optimality conditions for a simplified modeling framework are used to gain a deeper understanding of the implications of co-implementing an emissions cap with an RPS policy. A

simplified version of the generation expansion model is used in this section for illustration purposes alone. The model is specified with an objective function of minimizing the supply cost. The total supply cost is expressed as the sum of investment costs of new units, fixed costs of existing units and operational (including fuel) costs of operating units. The model assumes perfect cost foresight and competitive markets (i.e. operational costs equals the marginal cost of generation). Also, each firm is assumed to constitute of one type of generating technology. The energy and capacity availability constraints are common for all scenarios. The key decision variables are MWh to generate from available units (both new and existing units) in every time period and MW capacity of new capacity to invest in a given year. The first-order optimality conditions are outlined for three specific scenarios[40] (Rau, 2003; Mathworks, 2014). *Scenario 1* comprises of an emissions cap constraint alone (in addition to energy and capacity constraints). *Scenario 2* comprises of an RPS constraint alone while *Scenario 3* models both the RPS and emissions cap constraints. The detailed notations and problem formulation are presented below. Equation (1) is the objective function of the analytical model. Equations (2)-(5) represent the key constraints for this simplified model: energy, capacity, emissions and RPS. Equations (6)-(8) are the generalized first order optimality conditions for this analytical model.

***[1] Objective function***

$$\boldsymbol{minmize\ COST} = \sum_{r,y,t,i}\left(\left(\boldsymbol{MWh_{r,y,t,i}MC_{y,i}}\right) + \left(\boldsymbol{FC_{y,i}}\left(\boldsymbol{MW_{r,y,i}} + \boldsymbol{EX_{r,i}}\right)\right) + \left(\boldsymbol{IC_{y,i}MW_{r,y,i}}\right)\right) \qquad (1)$$

where

*r* is the index for state/sub-region

*y* is the index for years

[40] The first order optimality conditions are specified using Karush-Kuhn-Tucker (KKT) conditions. These are necessary (but *not sufficient* conditions) for finding the optimal solution. In addition, the system of constraints must also satisfy certain regularity conditions (known as constraint qualification) (See: Rau, 2003: pp.185-195, for theory behind Lagrange multipliers and KKT conditions). All convex problems (with linear equality constraints and convex inequality constraints) satisfy the regularity conditions. The sign and notation conventions used in this section are also based on Rau, 2003.

*t* is the index for time periods (summer, winter, spring, fall)

*i* is the index for firms/technologies (like nuclear, coal, wind, solar etc.)

$\boldsymbol{MWh_{r,y,t,i}}$ is the electricity generation of firm *i* in period *t* , year *y* and sub-region r (decision variable)

$\boldsymbol{MC_{y,i}}$ is the average marginal cost(including fuel and O&M costs) for firm *i* in year y

$\boldsymbol{FC_{i,y}}$is the fixed cost for firm *i* in year y

$\boldsymbol{MW_{r,y,i}}$ is the invested capacity of firm *i* in sub-region *r* and year y (decision variable)

$\boldsymbol{EX_{r,i}}$ is the existing capacity of unit *i* in sub-region r at the start of simulation.

$\boldsymbol{IC_{y,i}}$is the investment cost for one unit (one megawatt, 1 MW) of firm/technology *i* in year y

***[2] Energy constraints***

$$\sum_{\mathbf{i}} \mathbf{MWh_{r,y,t,i}} = \mathbf{Demand_{r,y,t}}\ \mathbf{RM}\ \forall\, \mathbf{r,y,t} \qquad \perp\ \boldsymbol{\beta_1} \tag{2}$$

where

$\mathbf{Demand_{r,y,t}}$ is the total demand for electricity in year y in time period t and sub-region r

$\boldsymbol{RM}$ is the reserve margin rate (greater than 1.0) (assumed uniform for all sub-regions)

***[3] Availability/Capacity constraints***

$$\mathbf{MWh_{r,y,t,i}} \leq \left(\left(\mathbf{EX_{r,i}} + \sum_{\mathbf{u}}^{\mathbf{y}} \mathbf{MW_{r,u,i}}\right)\mathbf{h_t CF_{t,i}}\right)\ \forall\, \mathbf{r,y,t,i} \qquad \perp\ \boldsymbol{\lambda_1} \tag{3}$$

where

u is an alias for set y

$\boldsymbol{h_t}$ is the number of hours in time period t

$\boldsymbol{CF_{t,i}}$is the capacity factor for firm i in time period t (between 0 and 1)

***[4] Emissions constraints***

$$\sum_{\mathbf{t,i}} \mathbf{ER_{i,j} MWh_{r,y,t,i}} \leq \mathbf{Ecap_{r,y,j}}\ \forall\, \mathbf{r,y,j} \qquad \perp\ \boldsymbol{\lambda_2} \tag{4}$$

where

$\boldsymbol{ER_{i,j}}$ is the amount that firm/technology i emits pollutant j for every unit (MWh) of generation

$\boldsymbol{Ecap_{y,j}}$is the total limit for the pollutant j in year y

***[5] RPS constraints***

$$\sum_{t,ren} \boldsymbol{MWh_{r,y,t,ren}} \geq \left(\boldsymbol{RPS_y}\ \sum_{t,i} \boldsymbol{MWh_{r,y,t,i}}\right)\ \forall\, \boldsymbol{r,y} \qquad \perp\ \boldsymbol{\lambda_3} \tag{5}$$

where

ren is a sub-set of i comprising of renewable technologies alone

$RPS_y$ is the minimum percentage of renewable generation set for year y (between 0 and 1)

The generalized KKT conditions are presented below:

$$\min \quad f(x)$$
$$s.t \quad h_j\ (x) = 0$$
$$g_k(x)\ \leq 0$$

*Condition 1:* $\frac{\partial\, L(MWh_{y,t,i},\lambda_i\,,\beta_j\,)}{\partial(MWh_{y,t,i})} = 0$ ; $\frac{\partial\, L(MW_{y,i},\lambda_i\,,\beta_j\,)}{\partial(MW_{y,i})} = 0$ (i.e. Lagrange Function)

$$\text{i.e. } \nabla f(x) + \sum_j \beta_j \nabla h_j(x) + \sum_k \lambda_k \nabla g_i(x) = 0 \tag{6}$$

*Condition 2:* $$\lambda_k g_k(x) = 0 \qquad \forall\ \mathbf{k} \tag{7}$$

*Condition 3:* $$h_j(x) = 0 \text{ and } \beta_j \neq 0 \quad \forall\ \mathbf{j}$$
$$g_k(x) \leq 0 \text{ and } \lambda_k\ \geq 0 \qquad \forall\ \mathbf{k} \tag{8}$$

Here $\lambda_k$ and $\beta_j$ are the Lagrange multipliers associated with the respective inequality and equality constraints[41]. In this model, the only equality constraint is the energy constraint. *Condition 1* is setting the Lagrange function of the decision variable and the corresponding multiplier to zero. *Condition 2* is called the complementary slackness condition and indicates that either $\lambda_k$ or g(x) or both must be equal to zero. Unlike the sign of $\lambda_k$, the sign of $\beta_j$ can either be positive or negative. The KKT conditions are derived for the two key decision variables ($MWh_{y,t,i}$, $MW_{y,i}$) under three different scenario themes. Since *Condition 3* is common for all scenarios, they are not repeated below (see Equation (8)). The KKT conditions under different scenarios themes are formulated below:

***Scenario 1: Only emission cap***

For $MWh_{r,y,t,i}$

*Condition 1:* $MC_{y,i} + \lambda_1 + \beta_1 + (\lambda_2 ER_{i,j}) = 0 \qquad \forall\ y, i, j$

*Condition 2:* $\lambda_1 \left(MWh_{r,y,t,i} - \left(\left(EX_i + \sum_{r,u} MW_{r,u,i}\right) h_t CF_{t,i}\right)\right) = 0 \qquad \forall\ r, y, t, i$

[41] Strictly speaking, the dual variables $\beta_j$ and $\lambda_k$ are a vector of dual variables corresponding to the constraints applied for every year and sub-region. A bold format of the dual variable denotes the corresponding vector.

$$\lambda_2\left( \left(\sum_{t,i} ER_{i,j} MWh_{r,y,t,i}\right) - Ecap_{y,j}\right) = 0 \qquad \forall\, r, y, t, i$$

For $MW_{r,y,i}$

*Condition 1:* $$FC_{y,i} + IC_{y,i} - \lambda_1\left(h_t CF_{t,i}\right) = 0 \qquad \forall\, y, t, i$$

*Condition 2:* $\lambda_1 g_1(x) = 0$ *and* $\lambda_2 g_2(x) = 0$ $\qquad \forall\, r, y, i$

***Scenario 2: Only RPS***

For $MWh_{r,y,t,i}$,

*Condition 1:* $$MC_{y,i} + \lambda_1 + \beta_1 + \left(\lambda_3\left(1 + RPS_y\right)\right) = 0 \qquad \forall\, y, i$$

*Condition 2:* $$\lambda_1\left(MWh_{r,y,t,i} - \left(\left(EX_i + \sum_u MW_{r,u,i}\right) h_t CF_{t,i}\right)\right) = 0 \qquad \forall\, r, y, t, i$$

$$\lambda_3\left(\left(\sum_{ren} MWh_{r,y,t,ren}\right) + \left(RPS_y \sum_{t,i} MWh_{r,y,t,i}\right)\right) = 0 \qquad \forall\, r, y, t, ren$$

For $MW_{r,y,i}$

*Condition 1:* $$FC_{y,i} + IC_{y,i} - \lambda_1\left(h_t CF_{t,i}\right) = 0 \qquad \forall\, y, t, i$$

*Condition 2:* $\lambda_1 g_1(x) = 0$ *and* $\lambda_3 g_3(x) = 0$ $\qquad \forall\, r, y, i$

***Scenario 3: With RPS and emissions cap***

For $MWh_{r,y,t,i}$

*Condition 1:* $$MC_{y,i} + \lambda_1 + \beta_1 + \left(\lambda_2 ER_{i,j}\right) + \left(\lambda_3\left(1 + RPS_y\right)\right) = 0 \qquad \forall\, y, i, j$$

*Condition 2:* $$\lambda_1\left(MWh_{r,y,t,i} - \left(\left(EX_i + \sum_u MW_{r,u,i}\right) h_t CF_{t,i}\right)\right) = 0 \qquad \forall\, r, y, t, i$$

$$\lambda_2\left(\left(\sum_{t,i} ER_{i,j} MWh_{r,y,t,i}\right) - Ecap_{y,j}\right) = 0 \qquad \forall\, r, y, t, i$$

$$\lambda_3\left(\left(\sum_{ren} MWh_{y,t,ren}\right) + \left(RPS_y \sum_{t,i} MWh_{r,y,t,i}\right)\right) = 0 \qquad \forall\, r, y, t, ren$$

For $MW_{r,y,i}$

*Condition 1:* $$FC_{y,i} + IC_{y,i} - \lambda_1\left(h_t CF_{t,i}\right) = 0 \qquad \forall\, y, t, i$$

*Condition 2:* $\lambda_1 g_1(x) = 0$; $\lambda_2 g_2(x) = 0$ *and* $\lambda_3 g_3(x) = 0$ $\qquad \forall\, r, y, t, i$

Some the key inferences from this analytical model are listed below:

- In a competitive market framework, $\boldsymbol{\lambda_1}$ is reflective of the wholesale electricity price component associated with the energy constraint. $\boldsymbol{\beta_1}$ is reflective of the wholesale electricity price component associated with the capacity constraint.
- $\boldsymbol{\lambda_2}$ and $\boldsymbol{\lambda_3}$ are the dual variables associated with the emissions cap and RPS constraints respectively. They are reflective of the marginal abatement cost associated with the reduction in $CO_2$ emissions by one unit (say 1 short-ton) or increase in RPS requirement by a unit (say 1 MWh of additional renewables generation).
- Under equivalent capacity and energy prices, the marginal cost of abatement in an emission cap only scenario is given by $\boldsymbol{\lambda_2} = -\frac{\boldsymbol{MC_{y,i}}}{\boldsymbol{ER_{i,j}}}$ (from *Scenario 1*). The marginal abatement cost of reducing $CO_2$ emissions is directly proportional to the marginal cost of generation for each technology and inversely proportional to the corresponding emissions rate for $CO_2$.
- Under equivalent capacity and energy prices, the marginal cost of abatement in a RPS only scenario constraint is given by, $\boldsymbol{\lambda_3} = -\frac{\boldsymbol{MC_{y,i}}}{(\boldsymbol{1+RPS_y})}$ (from *Scenario 2*). The marginal abatement cost of encouraging renewable generation is directly proportional to the marginal cost of generation for each technology and inversely proportional to the RPS fraction for the given year.
- Under an equivalent capacity and energy price component of wholesale price and a scenario involving both RPS and emissions cap (from *Scenario 3*),

  Marginal cost of abatement from an emissions cap $\boldsymbol{\lambda_2} = \frac{-\boldsymbol{MC_{y,i}} - \boldsymbol{\lambda_3}(\boldsymbol{RPS+1})}{\boldsymbol{ER_{i,j}}}$

  Marginal cost of abatement from a RPS instrument $\boldsymbol{\lambda_3} = \frac{-\boldsymbol{MC_{y,i}} - \boldsymbol{\lambda_2}\,\boldsymbol{ER_{i,j}}}{(\boldsymbol{1+RPS})}$

As seen above, the marginal abatement cost metrics are slightly complicated when the two policies are co-implemented. Also, in a co-implementation scenario there is a complementarity relationship between the two marginal abatement cost metrics (i.e. one depends on the other). One possible way to compare

and quantify the marginal cost metrics under different scenario themes is to use a *stylized example* of the cost and emissions characteristics of generation technologies in the Northeast region. Another approach is to run a computational model and verify the results. This is accomplished by using LP-CEM, a supply cost optimization for the Northeast region of the U.S (see Section 5.6). In this section, the marginal abatement cost metrics are derived using simplified cost and emissions assumptions listed in Table 5.2. For simplification these metrics are assumed to be constant for all years in the modeling simulation (2010-2040). The average abatement cost metrics are then compared with the computational model outcomes in Section 5.6.

**Table 5.2: Simplified cost and emissions assumptions for generation technologies in the U.S Northeast**

| **Generation technology** | **Share of total generation (2010-2040)** | **Marginal cost of generation (incl. fuel costs, O&M)** | **Emission Rate for $CO_2$ ($CO_2$-short tons /MWh)** |
|---|---|---|---|
| Coal | 0.08 | $ 35.60 | 0.75 |
| Natural Gas | 0.30 | $ 52.30 | 0.50 |
| Nuclear | 0.38 | $ 24.70 | - |
| Renewables (Hydro, On-shore wind and Solar) | 0.24 | $ 16.00 | - |

Note: Marginal cost estimates are based on non-capital cost component of LCOE estimates used in AEO-2014.

- For an emissions cap only scenario, the marginal abatement cost is given by weighted average estimate of $\frac{MC_{y,i}}{ER_{i,j}}$ for each generation technology. Since renewables and nuclear power have no associated $CO_2$ emissions, they can be ignored in this computation.

Marginal abatement cost of reducing $CO_2$ emissions using an emissions cap only policy

$$= Coal\ share * \frac{MC_{coal}}{ER_{coal}} + NG\ share * \frac{MC_{NG}}{ER_{NG}}$$

$$= (0.08 * \frac{35.6}{0.75} + 0.30 * \frac{52.3}{0.5})$$

$$= \$\ 35.17 \text{ per short-ton of } CO_2 \qquad (9)$$

- For an RPS only scenario, the marginal abatement cost is given by weighted average estimate of $\frac{MC_{y,i}}{(1+RPS_y)}$ for each generation technology. For simplification the RPS level is assumed to be 24% for all years in the modeling horizon.

Marginal abatement cost of encouraging renewables using RPS only policy

$$=Coal\ share * \frac{MC_{coal}}{1+RPS} + NG\ share * \frac{MC_{NG}}{1+RPS} + Nuclear\ share * \frac{MC_{Nuc}}{1+RPS} + Renewables * \frac{MC_{Ren}}{1+RPS}$$

$$= 0.08 * \frac{35.6}{1.24} + 0.30 * \frac{52.3}{1.24} + 0.38 * \frac{24.7}{1.24} + 0.24 * \frac{16}{1.24}$$

= $ 25.59 per MWh of renewables generation (10)

- For a scenario with both RPS and emissions cap,

Marginal abatement cost of encouraging renewables using a combination of RPS and emissions cap

$$= Coal\ share \left(\frac{MC_{coal}+\lambda_{cap}\ ER_{coal}}{(1+RPS)}\right) + NG\ share \left(\frac{MC_{NG}+\lambda_{cap}\ ER_{NG}}{(1+RPS)}\right) + Nuclear\ share \left(\frac{MC_{nuc}}{(1+RPS)}\right) + Renewable\ share * \left(\frac{MC_{Ren}}{(1+RPS)}\right)$$

$$= 0.08 * (\frac{35.6+(35.17*0.75)}{1.24}) + 0.30 * (\frac{52.3+(35.17*0.5)}{1.24}) + 0.38 * (\frac{24.7}{1.24}) + 0.24 * (\frac{16}{1.24})$$

= $ 31.54 per MWh of renewable generation (11)

Marginal abatement cost of reducing $CO_2$ emissions using a combination of RPS and emissions cap

$$= Coal\ share * \left(\frac{MC_{coal}+\lambda_{RPS}(RPS+1)}{ER_{coal}}\right) + NG\ share * \left(\frac{MC_{coal}+\lambda_{RPS}(RPS+1)}{ER_{coal}}\right)$$

$$= 0.08 * \frac{(35.6+(25.59*1.24)}{0.75} + 0.30 * \frac{52.3+(25.59*1.24)}{0.5})$$

= $ 57.59 per short-ton of $CO_2$ (12)

## 5.4 LP-CEM framework for plausible policy scenarios and marginal abatement cost analysis

LP-CEM is a generation/capacity expansion model that simulates the least-cost expansion of electric generation capacity. A detailed description of the model architecture, data assumptions and constraints formulation is presented in Chapter 4. LP-CEM is adapted to model the power sector trends for the eleven

states in the Northeast region for the years 2010-2050 (see Table 6.1 for a list of states). The cost and performance assumptions for different generating technology types are obtained from Energy Information Administration's Annual Energy Outlook 2014 (EIA-AEO, 2014). The input data for the current set of model runs are derived primarily from the Reference Case scenario of AEO-2014 report. The costs incurred in the future are discounted at a market rate of 6.5% (similar to model runs in Chapter 4). The RPS mandates are implemented at a state-level and are modeled as a minimum percentage of in-state renewable generation. The RGGI mandate is implemented using a region-wide cap with the states of New Jersey and Pennsylvania excluded. The proposed Clean Power Plan, however, is applicable to all states in the U.S. For the current set of simulation runs, it is assumed that New Jersey and Pennsylvania would join the RGGI consortium to take advantage of the emissions trading mechanisms. It should be noted that the scenarios explored in this chapter are *illustrative* in nature and states could come up with their own plan to achieve the required emissions reduction. There is also a possibility that New Jersey and/or Pennsylvania could join other regional cap-and-trade associations to meet the emission targets. Since RGGI has been implemented successfully for the last five years, it is most likely that the remaining nine Northeast states would continue in it for the foreseeable future as well.

In this chapter, the LP-CEM is executed for two distinct sets of analyses. For the first set of analysis, the model is adapted to incorporate the different assumptions concerning a regional cap-and-trade program and state-wide RPS policies (Section 5.5). These scenarios reflect the plausible policy scenarios for the region. For the second set, the model is executed for hypothetical RPS and emissions cap targets to plot the total abatement cost curve. Based on the abatement cost curves, the marginal cost of abatement was evaluated for each of three scenarios themes (i.e. RPS only, emissions cap only and a combination of RPS and emissions cap) (Section 6). The description of each scenario run for the first set of analysis is listed in Table 5.3. Under hypothetical *RPS* and *RGGI* scenarios, the model is executed with existing RPS schedule and RGGI mandated caps alone. These scenarios are highly unlikely since the region is already subject to

a combination of a RPS and a cap-and-trade program. These scenarios are used to provide a comparison basis to study the interaction effects of the policy instruments. The *RGGI+RPS* scenario is executed with the current RPS schedule in individual states and a RGGI mandated $CO_2$ cap through the year 2020. The RPS mandates are assumed constant beyond 2020 under this scenario. In an *RGGI+ RPS+Option1* scenario, a cap set by the Clean Power Plan rules under an *Option 1* pathway is applicable for years beyond 2020 (in addition to current RGGI and RPS mandates). States in the Northeast region are assumed to comply with the proposed regulations using a region-wide carbon cap and trade program. In an *RGGI+RPS+Option2* scenario, the cap beyond 2020 is set by the Option 2 pathway of Clean Power Plan. In an *RGGI+High RPS+Option1* scenario, the RPS mandates are assumed to increase at 1% percentage point a year until 2035 for individual states. This scenario is used to test the compliance costs under a scenario of high emission reductions and high RPS mandates (likewise for *RGGI+HighRPS+Option2* scenario). Modeling the weighted average emissions rate constraint as such, results in a non-linear formulation. To circumvent this problem, the emissions rate (lbs/MWh) are multiplied by the corresponding statewide baseline generation (MWh) amount and modeled as a mass based cap amount for carbon dioxide (in lbs). A region-wide cap allows for states with higher caps to generate more power and transmit the excess power to states with a binding cap. In effect, the LP-CEM framework allows for indirect trading of emissions allowances. Also, the current set of model runs do not account for other power sector pollutants like $SO_2$ and NOx.

**Table 5.3: Description of carbon cap and RPS scenarios**

| Scenario Name | Description |
|---|---|
| ***RPS*** | **A scenario with state-level RPS mandates alone** |
| ***RGGI*** | **A scenario with RGGI mandated regional caps alone** |
| ***RGGI+RPS*** | **A scenario with RGGI cap and current RPS mandates** |
| ***RGGI+ RPS+ Option 1*** | **A scenario with RGGI, Option 1 goals and current RPS mandates** |
| ***RGGI+ RPS+ Option 2*** | **A scenario with RGGI, Option 2 goals and current RPS mandates** |
| ***RGGI+ High RPS+ Option 1*** | **A scenario with RGGI, Option 1 goals+ Higher RPS mandates till 2035** |
| ***RGGI+ High RPS+ Option 2*** | **A scenario with RGGI, Option 2 goals+ Higher RPS mandates till 2035** |

**Note:** *Option 1* has a more stringent $CO_2$ emissions rate goal as compared to *Option 2*. Also, *Option 1* has a longer compliance period for achieving the final goal (in 2030) as compared to *Option 2* (in 2025).

## 5.4 Simulation results for plausible policy scenarios for the Northeast region

The simulation results of different emissions and RPS targets are presented in this section. The current RGGI carbon caps are mandated till the year 2020. The emissions rate set by the Clean Power Plan starts from the year 2020. Hence it is possible to model the effects of both RGGI and the proposed Clean Power Plan using the LP-CEM framework. In terms of the cap on the total $CO_2$ emissions, the Clean Power Plan imposes a more stringent target on statewide emissions as compared to the cap under RGGI. The RGGI mandated caps are imposed at the start of the simulation period. Also in the current set of model runs, a $CO_2$ cap is imposed on New Jersey and Pennsylvania starting from the year 2020. Figure 5.2 is a summary of the generation mix for the Northeast region for the years 2010, 2030 and 2050. Figure 5.3 plots the type of new capacity addition that is expected to occur under different scenario runs. Figures 5.4 and 5.5 plots the weighted average wholesale and renewable energy credit price for the Northeast region. These prices are derived as the post-optimality dual variables of the energy and RPS constraints respectively (see Rau, 2003; Wood et al., 2013, for theory and formulation behind dual variables).

**Figure 5.2: Electricity generation mix under different scenario runs (for the years 2010, 2030 & 2050)**

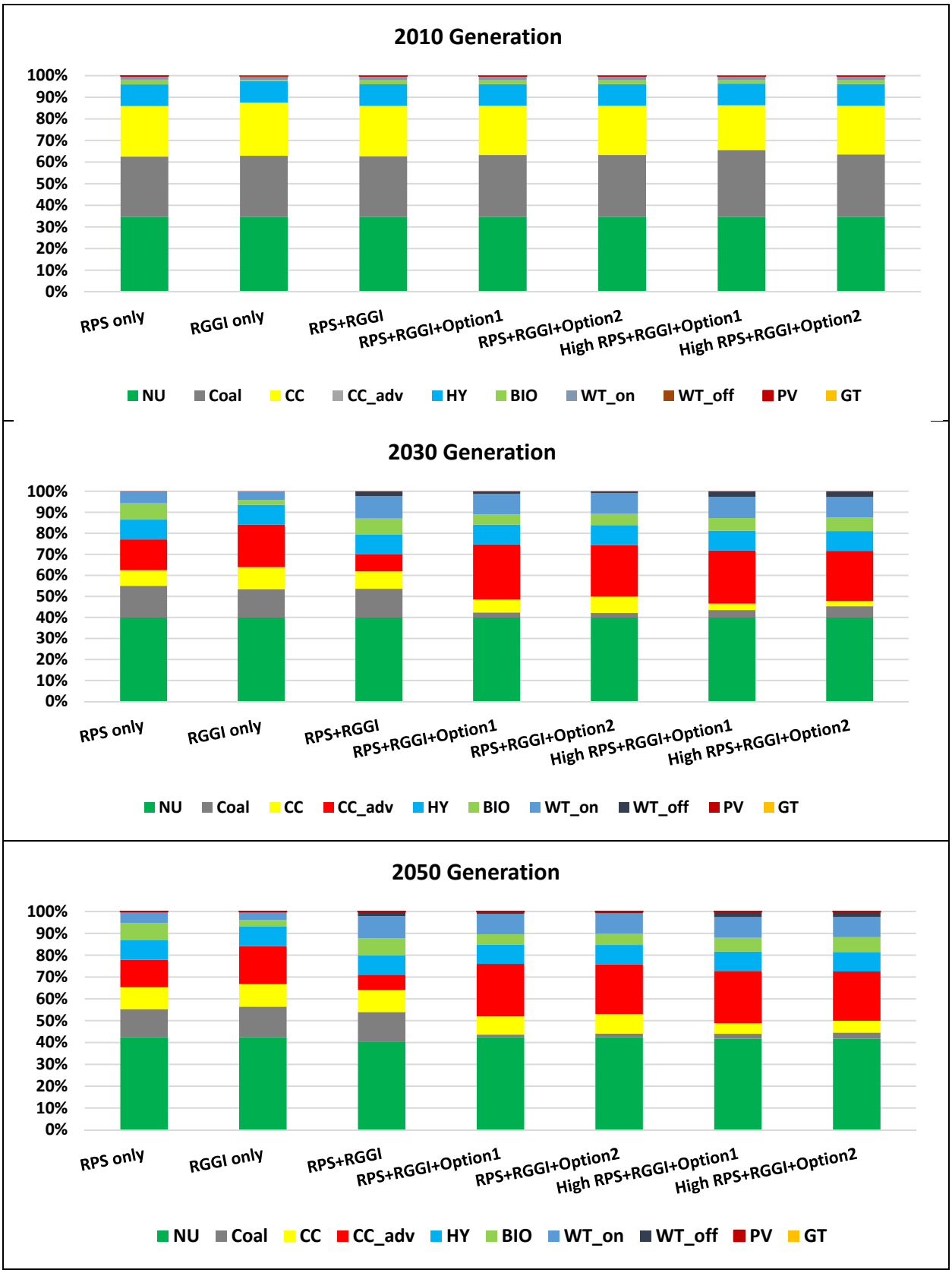


**Figure 5.3: Capacity addition trends (2010-50) under different scenario types**

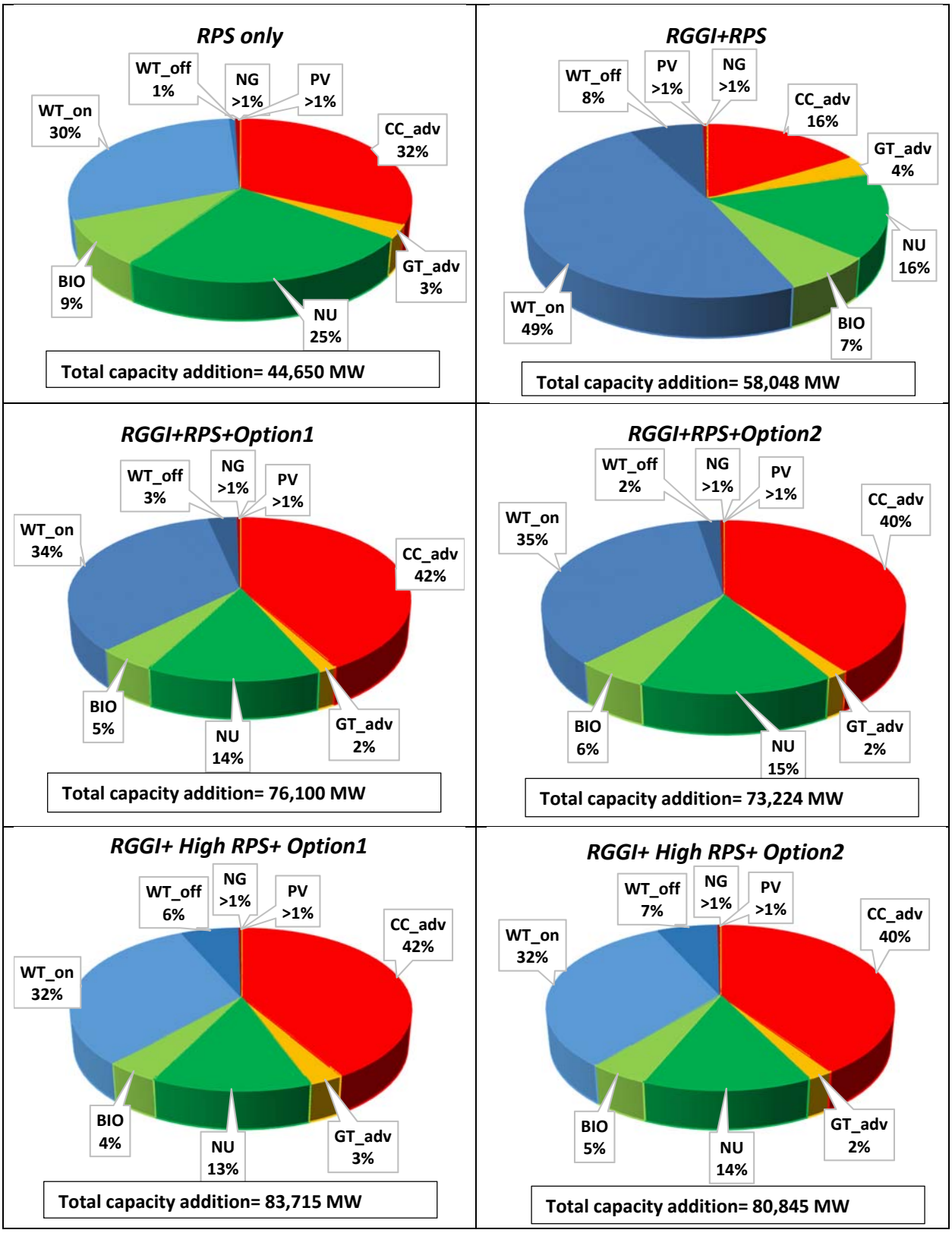


**Figure 5.4: Weighted average wholesale price trends for the Northeast region (2012 $/MWh)**

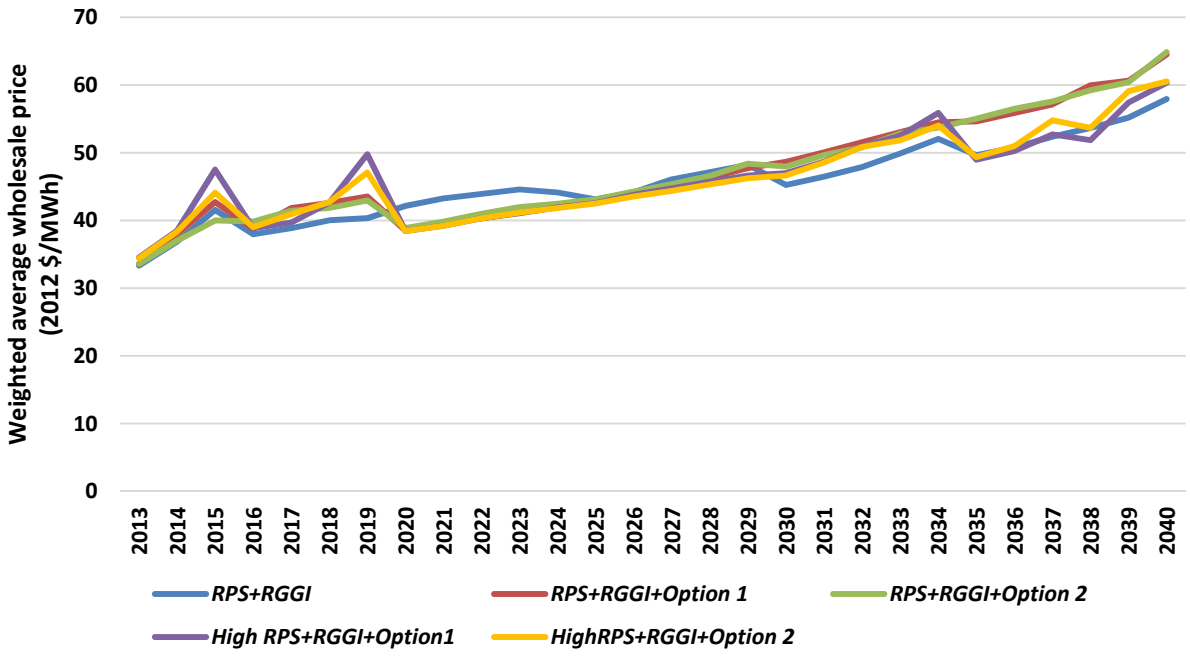



**Figure 5.5: Weighted average renewable energy credit (REC) price trends for the Northeast region**

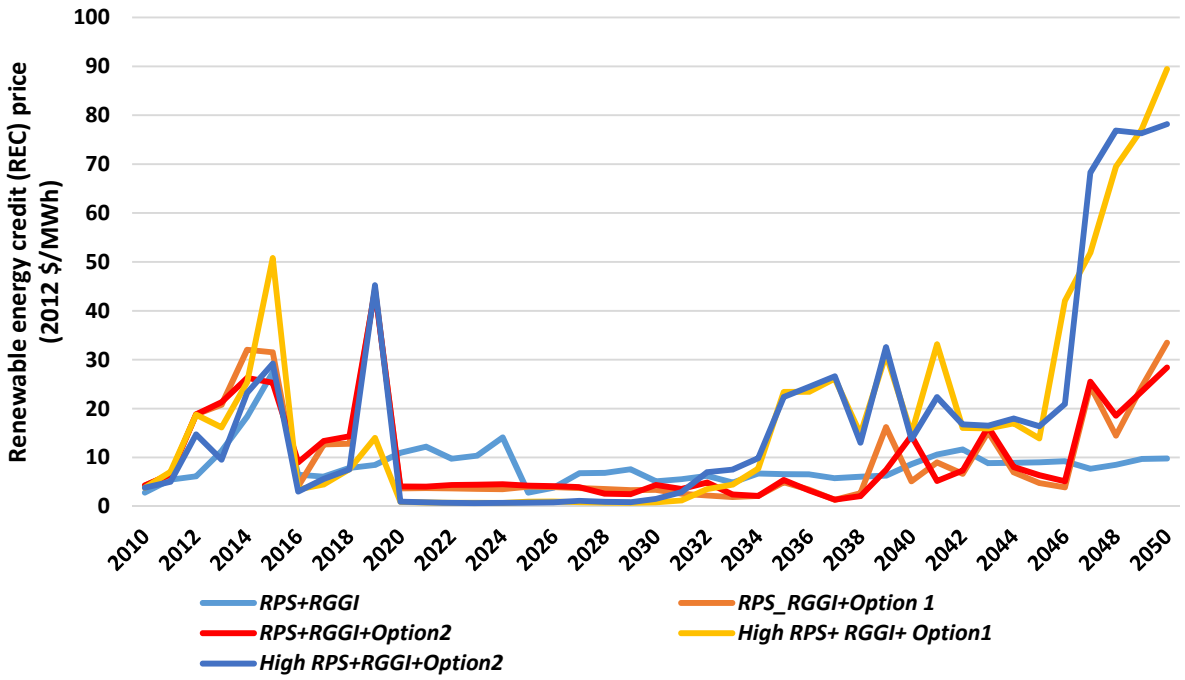


**Table 5.4: Comparison of total supply costs and prices for the Northeast region (2012 $)**

| Scenario Name | Total supply costs for 2010-50 (NPV 2012 $) | Total $CO_2$ emissions-Northeast power sector for 2010-50 (MT $CO_2$) | Wholesale energy price (2012 $/MWh) | | Renewable energy credit price (2012 $/MWh) | | $CO_2$ credit price (2012 $/short-ton $CO_2$) | | Combined electricity price (wholesale + policy program cost) (2012 $/MWh) | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 2030 | 2040 | 2030 | 2040 | 2030 | 2040 | 2030 | 2040 |
| ***RPS*** | **$ 842 billion** | **8,630.3** | **$48.02** | **$60.05** | **$11.51** | **$12.42** | **N.A** | **N.A** | **$59.53** | **$72.47** |
| ***RGGI*** | **$ 817 billion** | **8,452.5** | **$47.60** | **$58.71** | **N.A** | **N.A** | **$6.92** | **$6.82** | **$51.06** | **$62.12** |
| ***RGGI+RPS*** | **$ 866 billion** | **7,953.2** | **$45.24** | **$57.93** | **$5.15** | **$8.65** | **$1.02** | **$2.37** | **$50.90** | **$67.77** |
| ***RGGI+ RPS+ Option1*** | **$ 887 billion** | **6,658.5** | **$48.67** | **$64.48** | **$3.38** | **$5.13** | **$8.83** | **$27.27** | **$56.47** | **$83.25** |
| ***RGGI+ RPS+ Option2*** | **$ 881 billion** | **6,692.8** | **$47.95** | **$64.85** | **$4.39** | **$14.42** | **$6.62** | **$22.47** | **$55.65** | **$90.51** |
| ***RGGI+ High RPS+ Option1*** | **$ 904 billion** | **6,697.9** | **$46.97** | **$60.31** | **$0.82** | **$14.88** | **$5.43** | **$17.39** | **$50.51** | **$83.89** |
| ***RGGI+ High RPS+ Option2*** | **$ 901 billion** | **6,781.1** | **$46.64** | **$60.53** | **$1.55** | **$13.73** | **$4.19** | **$16.92** | **$50.29** | **$82.72** |

Note: Carbon credit prices represent the dual price of $CO_2$ emissions constraints imposed on the power sector alone. The prices are weighted average by the proportion of electricity demand from individual states. The carbon credit price on an MWh basis is approximately calculated based on the Clean Power Plan target of 1000 lbs/MWh for new power plants (not shown in the table). The total electricity price is the sum of wholesale energy, renewable credit and $CO_2$ credit prices (all in $/MWh).

From Figure 5.2, it is apparent that coal generation is likely to be phased out due to stringent emission goals under Clean Power Plan rules. In 2010, the average share of generation from coal units is about 12-15% of the total demand under different scenarios. With exception of the *RGGI+RPS* scenario, the percentage share of coal drops to 1-2% for years 2030 and 2050. This is due to the fact that coal generation from Pennsylvania is expected to be tightly constrained by the proposed Clean Power Plan rules. For the *RGGI+RPS* scenario, coal generation is expected to be around 6-7% for the years 2030 and 2050. Another trend that can be observed from Figure 5.2 is the replacement of the generation from conventional combined cycle units with advanced combined cycle units. These trends are also similar to the one observed for the LP-CEM runs for the Northeast under different economic and climate change projections (see Chapter 3). The share of advanced combined cycle generation is expected to be 11-13% for all scenarios with the proposed emissions cap.

From Figure 5.3, it can be inferred that the bulk of capacity addition in the future is likely to be advanced combined cycle, on-shore wind and nuclear. The nature of capacity addition is more or less similar under all Clean Power Plan scenarios. The amount of advanced combined cycle units added under different Clean Power Plan scenarios range from 30,000 MW to 34,000 MW. It should be noted that nuclear addition is subject to a modeling construction limit for the current set of scenarios. The limit is set at 3000 MW for every five year period starting from 2025. Overall, the capacity of nuclear addition to the region is about 9000-12,000 MW for the next forty years. The addition of nuclear is expected to serve the baseload demand in the future. Also, the interaction of a higher RPS policy mandate results in higher capacity addition of renewable resources like on-shore wind and solar. Since these renewable resources have a lower capacity factor, the overall MW addition is correspondingly higher for *High RPS* mandate scenarios.

Figure 5.4 projects the weighted average wholesale price trends under different scenario runs. When compared to the baseline scenario of *RPS+RGGI* alone, average wholesale prices are expected to increase due to Clean Power Plan rules. On average, the wholesale prices are expected to increase by 1-3% for

scenarios with emissions cap imposed by the proposed Clean Power Plan rules. It is interesting to note that the price increase is slightly lower for scenarios with higher RPS mandates, especially in the later years. The price spike in the initial years, especially around the year 2019, is due to Clean Power emissions targets that come into effect from the year 2020. A bulk of renewable capacity is added in 2020 to meet targets set by the proposed rules. For the years 2010-2050, the annual rate of price increase corresponds to about 2.1- 2.5%. Figure 5.5 plots the REC price trends for the Northeast region. On average, the high RPS scenarios are expected to have a higher REC price. The REC price spike towards the end reflects the binding nature of the RPS constraints in the later years (i.e. the model tries to optimize the costs by investing in just the amount of renewables required to meet the RPS requirement and system demand for the final year).

Table 5.4 provides a comparison of the overall supply costs under different scenario themes. As compared to a baseline scenario of RGGI and RPS mandates alone, the Clean Power Plan is likely to impose a cost increase on the ratepayers in the Northeast region. For 2030-2040, the average annual wholesale price increase is expected to range from 3-8% for scenarios with Clean Power Plan targets, as compared to a baseline scenario. An *Option2* pathway is likely to impose a lower overall supply cost on a long-term basis due to lower abatement targets. The overall supply cost is estimated to increase by $15-21 billion (NPV 2012 $) under assumptions of current RPS mandates. The supply cost increase is estimated to be $35-38 billion (NPV 2012 $) under assumptions of higher RPS mandates till 2035. For both these scenario themes, an *Option2* pathway is likely to result in a lower increase in overall societal costs. This could be due to the fact that accelerated deployment of renewables is likely to result in lower generation costs in the later years and avoids additional $CO_2$ abatement costs. Also, the total prices are lower under *High RPS* scenarios due to price suppression effect from greater renewable generation. When compared to a baseline scenario of *RGGI+RPS*, the total price increase is moderate by 2030 under different Clean Power Plan scenarios (assuming that the carbon and renewable credit prices are added to the wholesale price).

However, the increase in total electricity prices in 2040 ranges from 20-30% primarily due to high $CO_2$ credit prices in the later years. Since LP-CEM model does not factor-in other Clean Power Plan "building blocks" like energy efficiency or demand-side management, there is a distinct possibility that these projected carbon credit prices are over-estimated. Hence the final effect on long-term prices even under stringent emissions cap in the later years is likely to be less than the model projection.

## 5.6 Simulation results for marginal abatement cost analysis

For this section, the LP-CEM was executed with different RPS and emissions cap targets under three distinct scenario themes. The rationale behind these model runs is to plot the abatement cost curves- the total supply cost vs. policy target metric- for the power sector in the Northeast region for the years 2010-2050. The two policy targets analyzed include: cumulative $CO_2$ emissions from the power sector in the region and cumulative renewables based electricity generation in the region. These policy targets are good proxies to measure the abatement target achieved by RPS and emissions cap instrument. A total of thirty simulation runs were carried to plot the abatement cost curves. Figure 5.6 is a scatter plot of the total cumulative $CO_2$ emissions and total supply costs. Each point on the graph represents a simulation run of the LP-CEM model. The abatement cost curves are plotted using a linear and polynomial fit. Likewise Figure 5.7 is a scatter plot of total renewables generation and total supply costs. The slope of the linear fit equation indicates the marginal cost of abatement of the given policy instrument. For a polynomial fit, the interpretation is slightly complicated as it also depends on the emissions or renewable generation level. Some of the key quantitative inferences from the graphs are as follows:

- Using linear approximation, the marginal abatement cost of reducing the $CO_2$ emissions from the power sector by one short-ton of $CO_2$ using an emissions cap type instrument alone is equal to

$33.15[42]; using RPS-type instrument alone is equal to $ 40.88; and using a combination of RPS and emissions cap instruments is equal to $ 118.93 (all in 2012 $).

- Using linear approximation, the marginal abatement cost of increasing renewables electricity generation by one MWh using an emissions cap type instrument alone is equal to $ 95.53; using an RPS-type instrument alone is equal to $ 26.63; and using a combination of RPS and emissions cap instruments is equal to $ 55.38 (all in 2012 $).
- For an emissions cap and an RPS only scenarios, the marginal abatement cost estimates from the analytical model are comparable to the estimates derived from LP-CEM modeling simulation (see Eqs (9) and (10)). But under a scenario of co-implementation of an emissions cap and an RPS policy, the marginal abatement cost metrics are different for the two approaches.
- Using a polynomial approximation, the marginal abatement cost varies with the cumulative $CO_2$ emissions or renewables generation level. Since the polynomial function is quadratic, the marginal abatement curve has a constant slope (i.e. a linear marginal abatement curve).
- By equating the first differential of this function to zero, it is possible to obtain the policy targets corresponding to the minimum supply cost (i.e. the maximum cumulative $CO_2$ emissions level and minimum renewables generation for the Northeast region for the years 2010-2050). This corresponds to the point at which the marginal abatement costs are zero. The maximum cumulative $CO_2$ emissions level for the Northeast region is 7,601 MT $CO_2$ and the minimum quantity of cumulative renewables generation is 4,693 TWh for 2010-2050.

[42] The negative sign in the regression equation is reflective of the fact that it is a 1 short-ton *reduction* in $CO_2$.

**Figure 5.6: Abatement cost curves for $CO_2$ emissions reduction from the power sector in the U.S Northeast (linear and polynomial curve fit)**

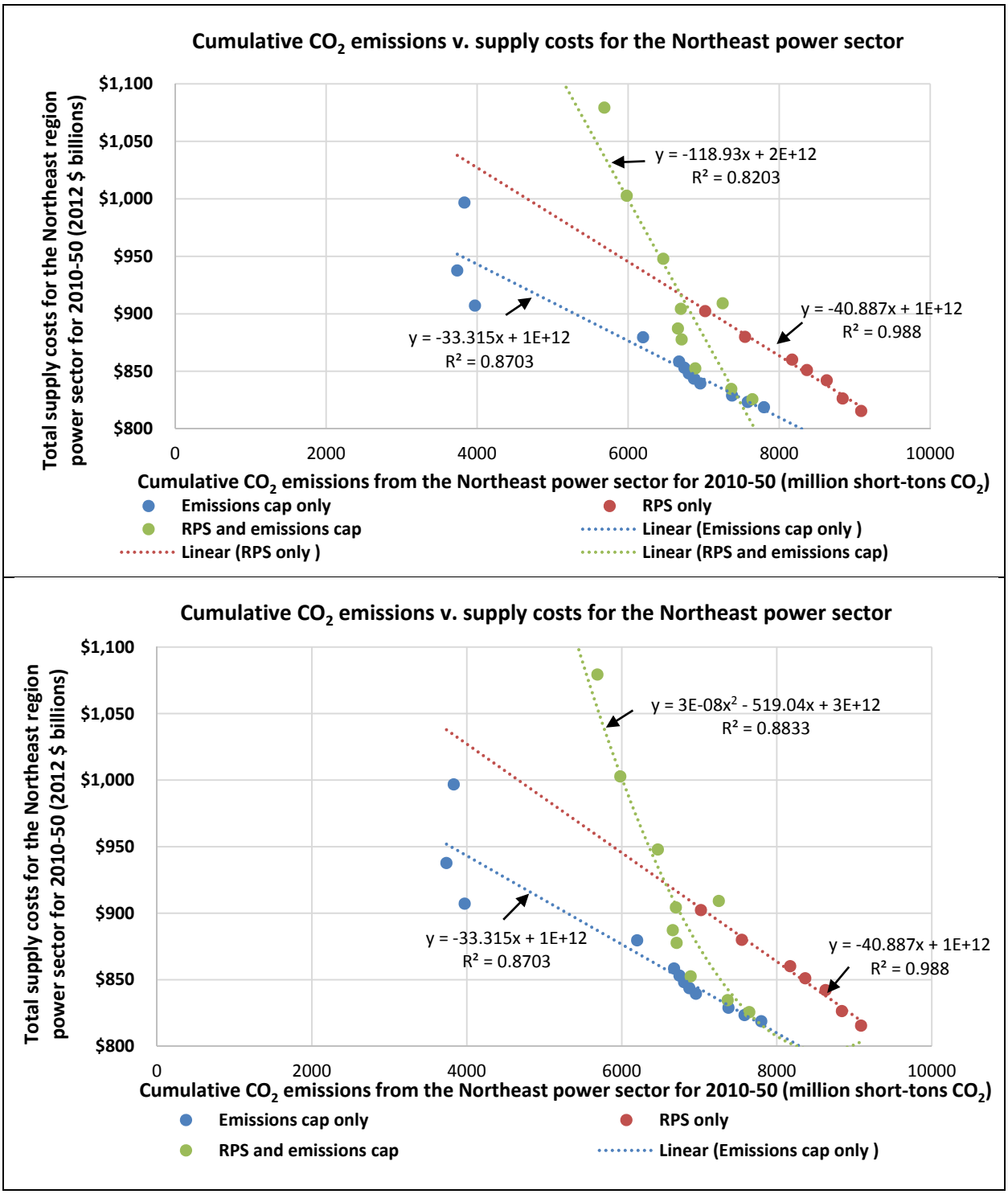
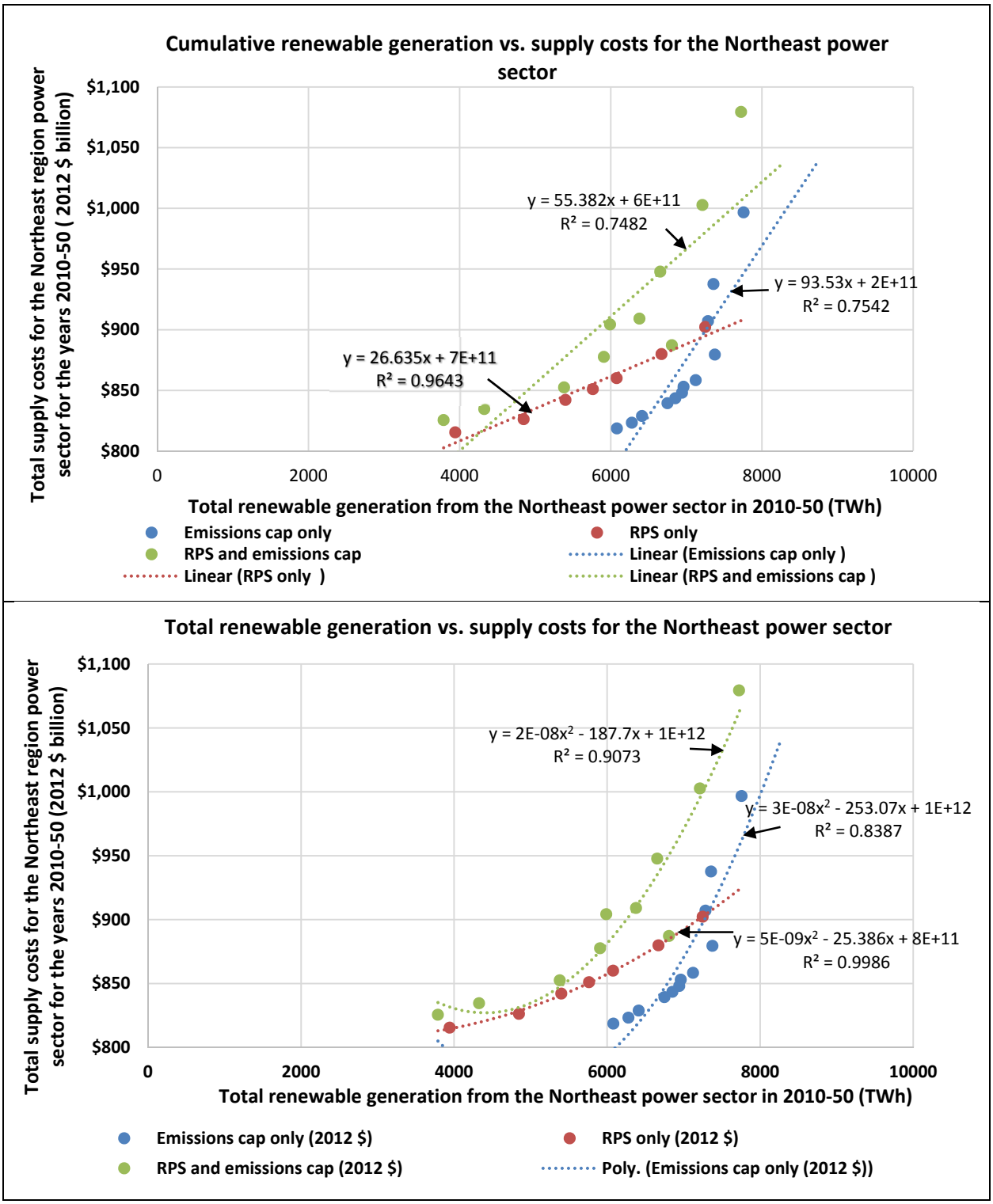


**Figure 5.7: Abatement cost curves for renewable generation from the power sector in the U.S Northeast (linear and polynomial fit)**



## 5.7 Summary

For this study, the LP-CEM model was executed under different assumptions of RPS and carbon cap policies. From a supply cost optimization perspective, the proposed Clean Power Plan is likely to result in a moderate increase in ratepayers' cost over the next forty years. Also, higher RPS mandates is likely to result in higher supply-side costs. A faster implementation of emissions goals results in lower overall societal costs for the Northeast region (but at a higher $CO_2$ emissions level). Thus, a combination of these policies is likely to have a beneficial effect for the final ratepayers in the region.

Some of the key findings of the LP-CEM model runs are summarized below.

- *A combination of an RPS policy and emissions cap does not lead to a substantial increase in wholesale prices (not the total price).* On average, the wholesale prices are expected to increase by 3-8% for scenarios with $CO_2$ emissions cap imposed by the proposed Clean Power Plan rules. The average price increase is comparatively lower for scenarios with higher RPS mandates (i.e. *Option 2* pathway of Clean Power Plan). This is due to the price suppression effect brought out by low or zero marginal cost renewable generation.

- *The effect on total price is however considerable if the cost of implementing the policy programs is socialized and recovered from the ratepayers.* Based on the estimates for the year 2040, the Clean Power Plan scenarios result in a final price increase of 20-30% as compared to a baseline scenario of *RGGI+RPS.* The bulk of this increase is due to the high incremental cost of $CO_2$ emissions in the later years when the cap is low and the overall demand is high. Since the other "building blocks" of Clean Power Plan like energy efficiency, plant heat rate improvement and demand-side management are not fully factored-in the LP-CEM, the $CO_2$ price increase is likely to be over-estimated.

- *The overall supply costs are lower for Option2 pathway with lower abatement targets and higher renewables deployment.* This is attributable to the fact that higher renewable addition results in lower generation costs. It should be noted that the current set of model runs does not factor in the intermittent nature of renewable generation. Also, the total price of electricity is lower in an *Option 2* pathway as compared to an *Option 1* pathway.

- *For the current set of scenario assumptions, nuclear power generation is critical for meeting the carbon caps in the Northeast region.* The power generated from nuclear power plants supplies nearly 40% of the total demand in the Northeast region. From an LP-CEM perspective, emissions-free power generation from baseload nuclear power plants is the most cost effective way to comply with the cap imposed by the proposed Clean Power Plan rules. As mentioned in Chapter 4, many of the nuclear plants in the region are expected to retire in coming decades. These retirements are not accounted for in the LP-CEM model runs. Also, the modeling construction limits on nuclear does not take into account the socio-political acceptance of new nuclear plants.

- *RPS-type instruments and carbon caps are cost effective in encouraging greater renewables generation.* At higher levels of renewables generation (i.e. above 7000 TWh for the Northeast region from 2010-2050), an RPS-type instrument is cost effective. For corresponding cumulative renewables generation below 7000 TWh, an emissions cap instrument is cost effective.

- *On the other hand, a carbon cap is the most cost-effective way to reduce $CO_2$ emissions from the power sector.* This is based on the marginal abatement cost metrics derived for the *RPS-only* and *Emissions caps-only* scenario themes (see Figure 5.6 and 5.7). This result is compatible with the existing literature on policy interaction effect (see Palmer and Burtraw, 2005; del Rio, 2007).

- For an *Emissions cap* and an *RPS-only* scenarios, the marginal abatement cost estimates from the analytical model are *comparable* to the estimates derived from LP-CEM modeling simulation (cf.

Eqs (9) and (10) and Section 5.6). However, in a co-implementation scenario there is a complementarity relationship between the two marginal abatement cost metrics (i.e. one is dependent on the other).

- For the years 2010-2050, the maximum cumulative $CO_2$ emissions level is equal to 7601 MT $CO_2$ and the minimum cumulative renewables generation is equal to 4693 TWh. There is a need to calibrate the RPS and emissions cap instrument design for the Northeast region with these target bounds under consideration.

- *The RPS and carbon cap policies are likely to benefit the Northeast region in the long-term.* From the current set of simulation runs, the interaction of RPS and carbon cap policies is expected to result in higher wholesale prices and supply costs. There are also other co-benefits to these policies like improvements in air quality, public health outcomes, fostering renewable energy innovation, boosting economic growth and grid resiliency. Hence the overall economy-wide benefits are likely to be higher from these policy interventions.

# Chapter 6

# A scoping study on other climate change impacts - extreme events and electricity markets

This chapter looks at some of the other impacts of climate change and variability that are *not* captured in the LP-CEM framework. This chapter is drafted as a scoping study for potential enhancements to the LP-CEM modeling framework. It covers two important aspects of power sector impact assessment: analyzing the implications of climate change and variability on the electricity market structure and analyzing the impacts of extreme events on the electric power sector.

- As highlighted in Chapter 2, the implications of climate change on electricity markets is not well explored in the literature. This chapter *conceptually* explores the possible future implications for PJM's institutional features and market structure. An overview of electricity market restructuring and regulation in the U.S is presented in this chapter for reader's benefit. The challenges associated with distributed generation and renewable intermittency are likely to emerge foremost on PJM's long-term planning agenda. This calls for capacity market design changes to ensure that the conventional resources are adequately compensated and remain financially viable in the future.
- Climate change, variability and extreme weather events have far-reaching consequences for the electric power sector. The recent experience of New York-New Jersey (NY-NJ) region with Hurricane Sandy is a wake-up call for institutions and policymakers to the vulnerabilities of the energy sector to extreme weather events. A synoptic summary of Hurricane Sandy and the widespread damage it has inflicted in this region is presented in this chapter for the reader's benefit. A set of policy recommendations is presented in the final section with the objective of informing forward-looking planning measures.

## 6.1 Introduction to electricity markets

The implications of climate change on electricity market structure can be studied under two broad categories. The first category analyzes the implications on the economic principles that underpin the market structure, and the second category analyzes the institutional framework of the market[43]. This categorization is somewhat artificial and overlapping as the institutional features that are implemented are derived directly from the underlying economic principles. Nevertheless, this format provides a structure and cogency to undertake this study. To further narrow down the scope of this chapter, I

[43] Kahn (1988) adopts a similar approach to study the economics of regulation.

propose to *conceptually* analyze the implications of climate change on PJM's market structure alone. PJM is the independent system operator for the Northeast region. PJM Interconnection performs a wide array of functions such as scheduling and dispatching wholesale generation; estimating the future system-wide demand; determining the locational marginal prices; administering the capacity and ancillary markets; scheduling transmission within the regional grid; allocating the cost of congestion among market participants; co-coordinating transmission and new capacity investment; monitoring the markets for non-competitive tendencies and implementing mitigation measures (Monitoring Analytics, 2011). A brief introduction on the evolution of the electric power sector, its regulatory framework and the rationale behind liberalization is also presented in this chapter.

## 6.2 Overview of power sector regulation and market restructuring

In the U.S., liberalization of public utilities has profoundly transformed the way electric power systems are structured and operated[44]. In terms of the underlying economic principles, liberalization involves a shift from recovering average cost of supply to that of recovering marginal cost of supply from ratepayers. Prior to liberalization, the rationale for economic regulation of the electric power sector was grounded on the fact that electric utilities are spatial monopolies. In this context, the cost of electricity supply is lowest when market demand is met by a single supplier in a given geographic area (Kahn, 1988: pp. 11-12). Also, it was thought that a monopolistic utility was more suited to tap into the economies of scale in electricity generation and supply. This thinking was predicated on the high sunk costs required to set up generation capacity. Under a "rate-base" arrangement, each utility was awarded a monopolistic franchise within a specified geographic area, usually based on historical presence or size of operation. Over the course of

[44] The term liberalization or de-regulation is used in the narrow sense of price regulation alone. This term does not encompass the technical regulations (like grid regulation) or other policy regulations (like environmental restrictions).

time, these franchisee-based utilities evolved as the vertically integrated companies with generation, distribution, transmission assets, and a dedicated retail customer base.

For decades since the commercialization of electricity, the real average price of electricity exhibited a steady decline (see EEI, 2006). As long as the declining price trend persisted, the rate-base regulation of vertically integrated utilities worked well. Under a rate-base regime, the utilities were guaranteed the opportunity to a "just and reasonable" return on the capital invested in new assets and operational costs incurred in meeting the consumer demand from existing assets. Under this scenario of declining average costs and high demand growth, the industry's main concern was on meeting the demand by investing in new assets. Starting in the mid-1970s, the average retail prices exhibited an upward trend (EEI, 2006 & Hogan, 2010). This upward price trend was due to decreasing returns to scale on the generation side, moderation of demand growth, and most importantly due to higher fuel prices (ibid.). The initial response to these price fluctuations was essentially to adapt the traditional rate base type of regulation to account for fuel fluctuations. But increasing capital costs of new investments and saturation in economies of scale in power plant size led to a sustained increase in regulated ratepayer tariff (Kahn, 1988; Borenstein and Bushnell, 2000). Thus, new capacity investments that were once deemed prudent under a "rate-base" regime ironically started to contribute to rising average costs. Also utilities under a regulatory regime had the perverse incentive of expanding their "rate-base" (by means of excess capital investments) on which they are entitled to earn a rate of return from ratepayers. As Averch, Johnson and Wellisz, among others, have pointed out, this tendency could lead to electric utilities to adopt an excessively capital-intensive technology and consequently pass on the higher retail rates to final ratepayers (see Averch and Johnson, 1962; Wellisz, 1963; Kahn, 1988).

These underlying market changes accompanied by an overall macro-economic policy shift towards liberalization, led to the restructuring of electricity markets in the U.S starting in the early 1980s (see

Joskow and Schmalensee, 1983; Borenstein and Bushnell, 2000). Restructuring involves transitioning from a franchisee-based monopolistic system to a market competition based system of electricity markets. Under a restructured market, the ownership and/or operation of generation, transmission and distribution assets is separated to ensure a fair and competitive electricity markets. Also, it was thought that a restructured competitive market could reduce some of the market inefficiencies on the *production* and *pricing* aspects of the power sector. On the production aspect, a restructured market is expected to yield a more efficient unit commitment and dispatch schedule, and also improve the performance of generating units. A centralized power pooling arrangement with economic least-cost dispatch is expected to reduce the supply costs of electricity. A restructured market is also expected to introduce incentives for better availability of generating plants, lower the non-fuel operating costs and improve the heat rates (Joskow, 2006). On the pricing aspect, the rates in a competitive restructured markets are based on marginal costs instead of the total average costs for a rate-base regulatory regime. Wholesale prices in a rate regulated environment fail to account for congestion effects and fuel costs fluctuations. Also as explained earlier, the cost-of-service rates offered a perverse incentive for utilities to invest in excessive capacity investments. The restructured markets helped to mitigate these inefficiencies substantially.

As of 2012, there are 2,189 traditional utilities in the U.S responsible for reliable and adequate supply of electricity to over 145 million customers of various classes[45]. These traditional utilities can be investor-owned, publicly-owned (usually at a municipal level); consumer-owned co-operatives or Federally-owned. These traditional utilities are subject to Federal, state and local laws on various aspects ranging from corporate practices to local environmental impacts. One of the earliest Federal regulation of electric power sector is the Federal Power Act (FPA) of 1920. This act established the Federal Power Agency (now renamed the Federal Energy Regulatory Commission (FERC)) as the federal regulator of the electric power

[45] US Energy Information Administration- Form 861 (2012)- http://www.eia.gov/electricity/data/eia861/

sector. Presently, the interstate sale of electricity on the wholesale market between utilities is regulated by FERC (except for Texas ERCOT which is not operationally synchronized with the rest of the country). FERC also regulates interstate transmission, hydro-electric licensing, issue regulations for grid reliability and oversees market and operational practices of system operators. The Public Utility Holding Companies Act (PUHCA) of 1935, cements the franchisee-based monopolistic structure of electric utilities by restricting them to specified geographic areas and requiring them to divest other "unregulated businesses". The PUHCA, which is now repealed, also imposed moderate barriers for non-utility companies from entering the power sector. Another consequence of PUCHA is to confine the utilities to operate within a single state and thereby subjecting them to state regulation through state-level public utilities commission (PUCs). The real impetus for market restructuring of the electric power sector is the Public Utility Regulatory Policies Act (PURPA) of 1978. PURPA opened up the generation sector to independent power producers (known as "qualifying facilities") and co-generation units (Joskow, 2006). The entry of private, non-utility players into the sector helped to set stage for further market restructuring reforms. The Energy Policy Act (EP Act) of 1992 is a milestone in the restructuring process as it opened up the wholesale market to private generators of all generating technology types. It also opened up the transmission sector for "wheeling" (or bulk transmission) services for non-utility players. FERC Orders 888/889 operationalized the provisions of EP Act (1992) by creating an "open and non-discriminatory access" to transmission lines, and a centralized dispatch system for scheduling transmissions (ibid.). FERC Order 2000, issued in 1999, implicitly requires all transmission utilities under its jurisdiction to join a regional power pool for reliability purposes. As a direct consequence of these structural changes, existing voluntary power-pools (like the PJM) transformed into the Independent System Operators (ISOs)/Regional Transmission Operators (RTOs) of today. A typical regulatory structure of a cost-of-service regime and a restructured competitive regime is shown in Figures 6.1 and 6.2 respectively. Figure 6.3 summarizes the key legislative and regulatory milestones in the restructuring process of the electric power sector.

**Figure 6.1: Regulatory structure of a typical cost-of-service regime in the U.S.**

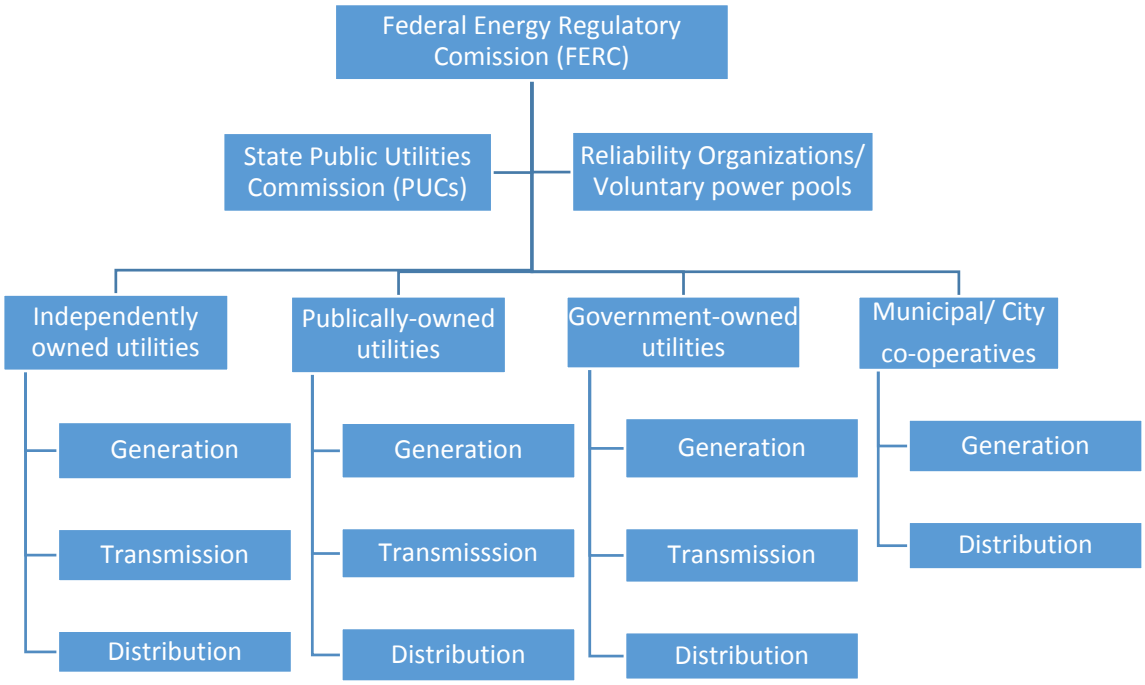



**Figure 6.2: Regulatory structure of a typical restructured competitive regime in the U.S.**

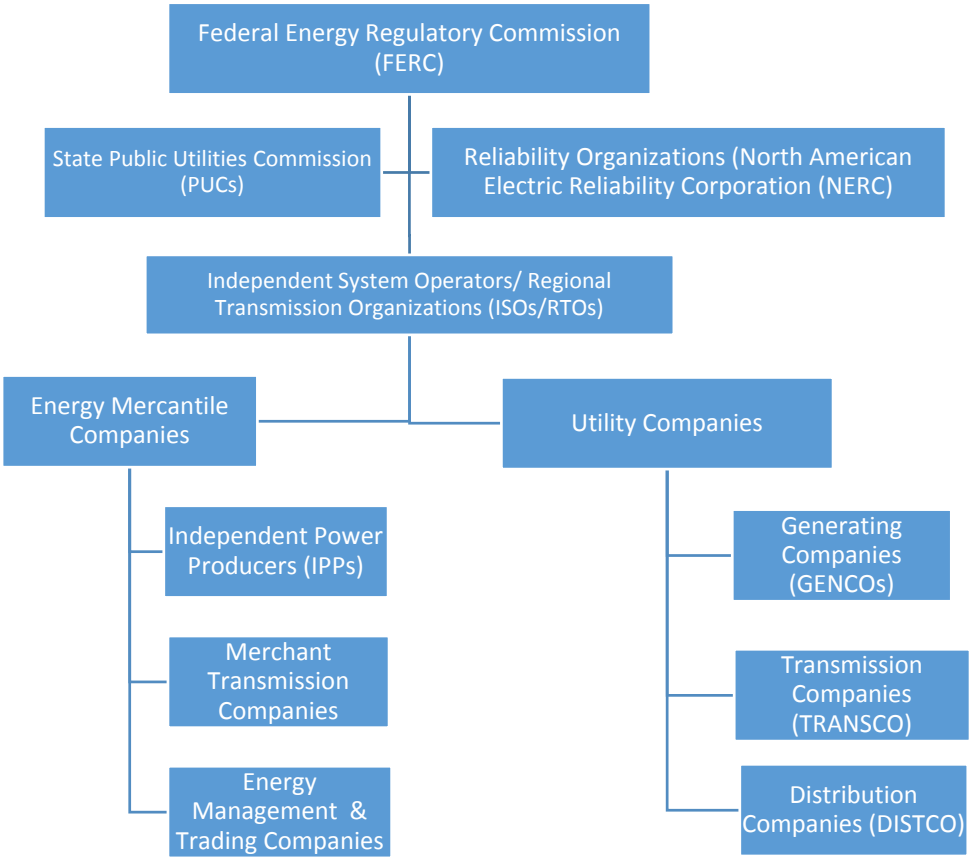


**Figure 6.3: Key legislative and regulatory milestones in the restructuring of the electric power sector**

| | |
|---|---|
| FPA (1920) | •Creates a federal regulator called the Federal Power Agency (now called Federal Energy Regulatory Commission (FERC))<br>•Under FPA, the federal government has jurisdiction over interstate sale of electricity, interstate transmission, and hydro-electrtic licensing |
| PUCHA (1935) | •Cements the franchisee-based monopolistic structures of utilities<br>•Divests utilities from engaging in unregulated businesses<br>• Creates regulatory barriers for utility consolidation and entry of non-utility companies into the sector |
| PURPA (1978) | •Opens up the generation sector for independent power producers (IPPs), especially renewables and co-generation units<br>•Requires regulated utilites to pruchase power from unaffiliated companies ("qualifying facilities") at prices that are based on utility's avoided costs |
| EP Act (1992) | •Opens up the wholesale sector for all types of generators<br>•Empowers FERC with the mandate to manage and regulate the interstate transmission network |
| FERC Order 888/889 (1996) | •Opens up the transmission network for all types of wholesale suppliers on an "open and non-discriminatory" manner<br>•Creates OASIS- a centralized information system- for scheduling wholesale power through the transmisison network<br>•Creates a regulatory framework to recover the "stranded costs" (i.e. fixed costs) incurred by ulities under a rate-base regime |
| FERC Order 2000 (1999) | •Formulates the guidelines for ISOs/RTOs<br>•Defines the set of functions that an ISO/RTO should assume |
| EP Act (2005) | •Repeals PUHCA<br>•Empowers FERC with jurisdictions over reliability standards; transmission planning and investments |

Source: Joskow, 2006; Kwoka, 2006.

## 6.3 Implications on competitive electricity market features

As discussed earlier, the grid reliability at a region-level is enforced by ISOs/RTOs. For New Jersey's case, it is governed by an ISO called PJM Interconnection that handles the wholesale operations of the grid and also regulates the competitive wholesale market. PJM handles wholesale movement of electricity in all or parts of thirteen states and District of Columbia in the Mid-Atlantic region. The PJM energy markets, like

most other ISO/RTO type markets, are organized based on the principles of market competition. The PJM energy markets comprises of the sale and purchase of electricity on the spot markets (i.e. the day-ahead (DA) and real time (RT)); bilateral markets and the forward markets (Monitoring Analytics, 2011). The competitive framework hinges on the principle of equating the price of the good to the marginal costs of meeting the demand[46]. For the electricity market, this would translate as the marginal variable cost of the last generator unit that is dispatched to meet the system demand (Hogan, 1998). In 1997, PJM started to facilitate trade between regulated utilities and independent power producers in a centralized spot market (Mansur, 2007). To account for transmission constraints, a "nodal" pricing system was put in place in the summer of 1998 (ibid.). By 1998, the PJM spot market had instituted most of the required design features for a competitive market, at least on the generation side. The centerpiece of a competitive spot markets is a "bid-based, security-constrained, economic dispatch with nodal prices" (Hogan, 2008). The key elements of a competitive wholesale market includes (also see Hogan, 1998; Joskow, 2006):

- A short-term spot market to dispense the variable energy costs to generators
- Spot market transactions are carried out at locational marginal prices (LMPs) which account for the network losses and congestion
- A two-settlement spot market system (i.e. day ahead (DA) and real-time(RT)) using day-ahead bidding prices and real-time balancing at the real-time prices
- A long-term capacity market for ensuring capacity adequacy to meet the future demand
- Bilateral transactions on the network are charged a usage charge that is equal to the difference in the LMPs at source and destination (in addition to agreed contract prices)
- Cost of ancillary services and transmission access are recovered on a socialized cost basis

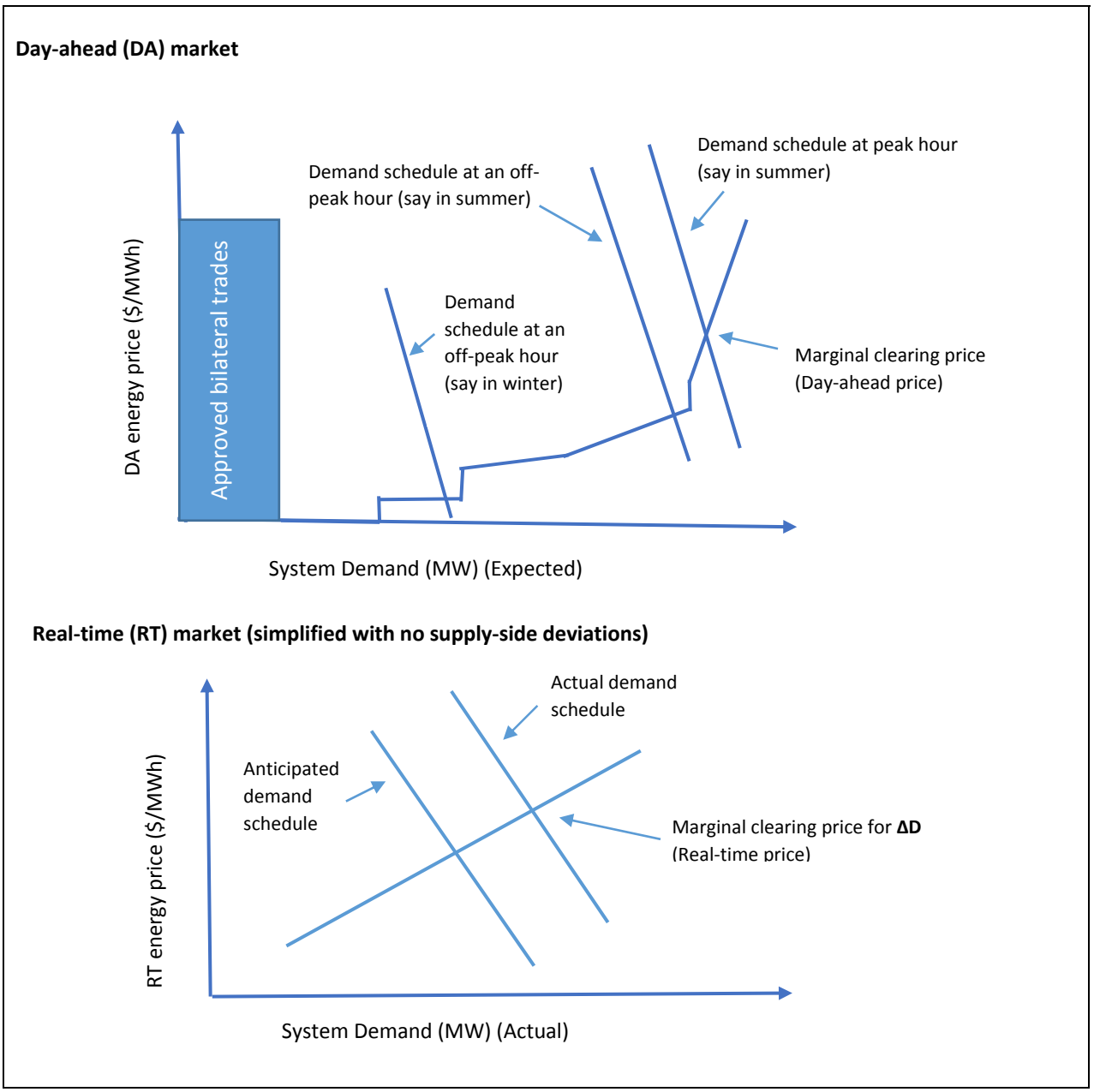
[46] For an introduction to marginal cost pricing, see Pindyck and Rubinfeld (2005) & Kahn(1988).

The competitive market dynamics can be conveniently analyzed under *two* distinct frameworks: short-run spot market and long-run capacity/contracts market. In the short-run spot market, the system operator balances the demand bids from load serving entities (LSEs) (i.e. customers) and supply offers from generators to arrive at a cost-effective dispatch schedule. Generators incur a variable cost when generating power. Stacking these variable costs in an ascending order for different generation technologies, we get the "merit-order" of dispatch. The demand schedule at each short-run time interval is relatively inelastic in most ISO/RTO-type market settings[47]. The short-run market dynamics are represented in Figure 6.4. The intersection of the two curves is the marginal clearing price for the entire market (assuming a simple of case of no congestion effects). As long as there are enough generators in the market and no single generator has undue influence on the marginal clearing price, the optimal offer of each generator reflects the true marginal cost of supply. Generators bidding more than the clearing price would run the risk of not being dispatched. Generators bidding less than their marginal cost of supply would run the risk of operating the units at a loss, if the marginal clearing price is lower than the marginal cost of supply. Hence in the short run, the competitive framework forces the generators to align their offers to their short run marginal costs (SRMC), in the absence of any market power or concentration. Marginal clearing price varies from one time interval to another due to changing overall system demand. Any deviations from the scheduled dispatch are settled in the real-time (RT) spot market with the corresponding real-time marginal clearing price. Non-convexities in the cost of production like start-up costs, incremental block bidding and non-continuous ramp-up/ ramp-down rates does introduce a degree of economic inefficiency in this framework. PJM market structure has mitigated these non-convexities to a considerable extent by taking cost increments into consideration while computing the economic dispatch schedule. These cost increments are in the form of start-up costs, ramp-up rates and incremental

[47] See Joskow (2006b). The capacity resources participating in demand response (DR) programs is relatively low in most of ISO/RTO type markets. Hence the demand schedule is assumed to be relatively inelastic.

energy output bids. In addition, the units in PJM are also paid an out-of-market "energy uplift" charges to ensure that the dispatching generation resources are not operated at an out-of-pocket loss. The implications on the long-run capacity markets are discussed under institutional framework in the next section (Section 6.4).

**Figure 6.4: Graphical illustration of a short-run electricity market (an energy market without congestion)**

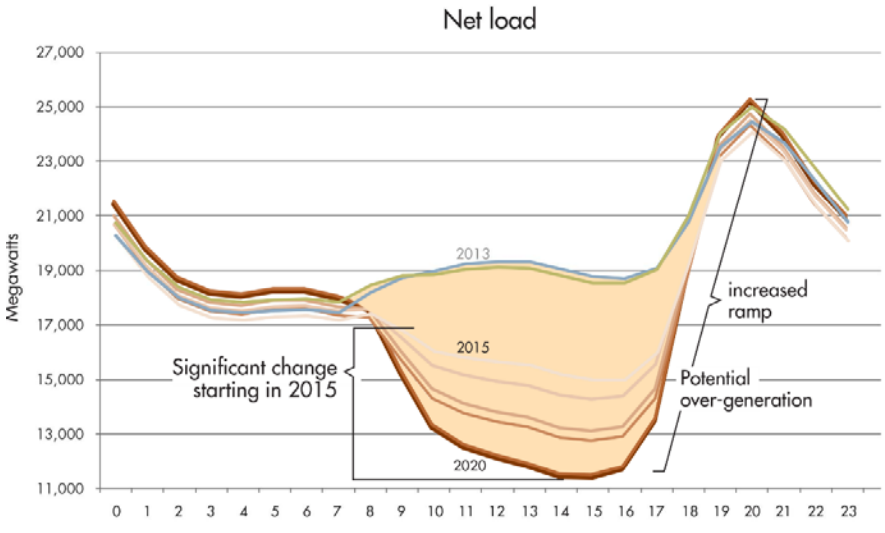


Climate change mitigation and adaptation efforts may create their own set of unintended consequences on this market framework. As outlined in the literature review chapter, electricity demand is highly dependent on the weather outcomes. The effects of climate change on the short-run spot markets can be summarized under *three* points. First, the increased peak system demand is likely to exert upward pressure on spot market prices. In the Northeast region, warmer winter and extended summer/dry season is likely to result in an annual double peak demand pattern, with a high summer peak and relatively lower winter peak. As shown in Figure 6.4, a slight increase in system demand in the peak period can have a major impact on the spot market prices. This is because the marginal unit that sets the market price is typically a combustion turbine, which has a high fuel and operating cost. Increasing usage of air conditioners in the Northeast region will lead to sustained increase in spot market prices in summers (Sailor and Pavlova (2003); US GCRP (2012); DOE (2013)). Second, the increased variation in system demand in any given period (say in a year) is likely to result in a more volatile spot market. As shown in the case of load duration curves (LDCs) for New Jersey in Chapter 3, inter-hourly volatility in system demand is likely to increase in the coming decades due to increased peak demand, economic growth, and climate change effects. The short-term variations in system demand are likely to cause price volatilities in the spot markets due to recurring starting costs and ancillary services costs like operating reserves. Finally, the increasing penetration of renewable resources constrains the ability of the system operator to respond to demand or supply fluctuations. Intermittent renewable resources pose a serious challenge to the overall grid reliability. As seen in the LP-CEM model runs, the renewable resources that are likely to be added in the Northeast region are primarily on-shore wind, hydro and solar. Also, the variability in generation will not always correspond to the variation in electricity demand. The problem of renewable intermittency is likely to be more pronounced in the coming years due to the compounding effects of emissions mitigation measures. These interaction effects are context-dependent and are explored in greater detail using the LP-CEM framework in Chapter 5. Since renewable intermittency is an important

area of concern for future electricity markets, the interaction effects are explained in detail using a demand vs. supply curve in this section. In the next section, I will revisit these concepts using a load duration curve (LDC) framework.

A carbon-constrained future is likely to attract new renewable generation resources. The major renewable technologies that are likely to be installed in the Northeast region include on-shore wind, solar photovoltaic (PV) and biomass. Conventional units with carbon capture and sequestration are also likely to be installed in the near future. Based on current investment/operational cost trends, wind and solar resources are likely to be deployed in large-scale in the coming decades. Large- scale integration of renewable technologies presents a host of operational and reliability challenges for ISOs/RTOs. Milligan et al. (2009) analyzed the impact of a 20% wind penetration on the Eastern Interconnection (to which PJM belongs). The study shows a reduction in spot prices and production costs at a 20% wind penetration level for the Eastern grid. A higher penetration rate (of around 30%) requires additional transmission infrastructure and better wind forecasting methodology. Wind resources tend to reduce carbon emissions as they displace fossil fuel generation. The study showed that the generation from wind resources in most simulation runs did not correspond with the system demand requirements. With conventional technologies (like nuclear or coal) it is possible to schedule the maintenance time to minimize the impact on peak load generation. In the absence of cost effective and large-scale energy storage technologies, this problem is even more acute. Milligan et al. (2009) have shown that at higher levels of wind penetration (at 20%-30% of total demand), managing the variability in output becomes a tough challenge for system operators.

**Figure 6.5: Effect of renewable intermittency on system supply and demand schedule**




Source: Image reproduced from Rothleder (2013)

The effect of renewable intermittency on the electric power system can be explained using the "duck graph" developed by the California Independent System Operator (CA-ISO) (Figure 6.5) (Rothleder, 2013; CAISO, 2014). The X-axis denotes the hours in a single day. The Y-axis denotes the total system demand *net* of renewable energy generation (i.e. the net load in MW). The net load denotes the variable portion of the overall demand that a system operator must balance in real time. To ensure the overall grid reliability, the system operator dispatches conventional generators (i.e. fossil and hydro units) to meet the net load. The "duck graph" (shown in Figure 6.5) consists of intra-day net load curves plotted for California for a sample representative day in March for the years 2013-20. With growing renewables penetration, there are higher levels of non-controllable and intermittent resources in the grid. The shaded portion in the graph represents the increased level of solar power generation during daylight hours in the coming years. As the sun sets and solar generation ends, the dispatchable resources must ramp-up their production to meet the system demand in the evening hours (the arch of the "duck's neck"). This calls for dispatchable generation resources with quick ramping flexibilities. Also, the graph shows a total of four demand ramps (two upward and two downward) in a single day. This calls for generation resources that

can start and stop multiple times in a given day. Variability from an intermittent output *per se* is not a problem for a system operator to handle. But it is the time scale of variations and the predictability of variations that constitutes the intractable aspect of the intermittency problem. For the PJM market, the fastest operating reserve has a maximum of ten minutes ramp-up time. If there are major variations in system-wide renewables output in less than ten minutes, there is a high risk of system-wide imbalance. This problem gets magnified at higher penetration levels. This intermittency also poses a problem when there is a drastic surge in the output of renewable resources as well. In this case, the system ends up producing excessive generation leading to a grid imbalance.

## 6.4 Implications on the institutional features of PJM

### i. Energy Markets:

The PJM energy market comprises of the sale and purchase of electricity on the spot markets (i.e. the Day-ahead (DA) and real time (RT)), bilateral markets and the forward markets (Monitoring Analytics, 2011). The generalized energy market design feature was explained in the previous section. LMPs on the spot markets constitute the benchmark price with which market transactions in other bilateral markets are settled. LMPs capture the cost of serving the next MWh of load at a specific location (or node) in the grid using the least cost mix of generation, while satisfying transmission and other technical constraints (for technical literature on LMPs see Schweppe et al., 1988). When there is no congestion in the system, the market clearing LMP would be the same at all nodes in the grid (except for the cost of marginal transmissions losses). In a competitive market, this system-wide LMP must be equal to the marginal cost of the last generator that came online to meet the system demand[48]. However, in reality most of the nodes in the grid are subject to some kind of binding transmission constraints at all times resulting in wide variations in nodal LMPs across the grid.

[48] System demand also includes sufficient operating reserves for reliability purposes.

Large-scale deployment of renewable generation resources is expected to lower the LMPs in PJM's energy market (PJM, 2009; Sotkiewiez, 2012). This is termed as price-suppression effect in the literature. It is caused by low or zero marginal cost renewable generation displacing higher marginal cost conventional generation, thereby lowering the energy component of electricity prices (see Jensen and Skytte, 2003; Miera et al., 2008; Felder, 2011). Counteracting this reduction in energy costs is the increase in dispatch costs to account for variability in intermittent generation, ensuring adequate operating reserves and overall system reliability. To study the implications of renewable intermittency on system demand, consider a typical load duration curve (LDC) for a region[49]. An LDC is a curve (see Figure 2.4 in Chapter 2) in which the load or the demand data for a given time interval is arranged in a descending order of magnitude. The area under the curve denotes the MWh energy consumption/demand in a given time frame (usually a year). Renewables resources like solar and wind are termed as intermittent resources, as their generation output depend on availability of natural resources. On the other hand, fossil-fuel and pumped storage hydro-units are termed as dispatchable resources, since their output can be directed by the system operator based on system demand and reliability requirements. The generation output from base-load units like nuclear and certain large coal plants are fixed in the short-run and cannot be varied/started/stopped frequently. A hypothetical LDC is plotted for the PJM region in Figure 6.6, highlighting the system demand curve with and without the intermittent generation. The figure assumes there are four types of generation resources that can meet the total system demand: a base-load generation (consisting of nuclear and large coal units); intermediate generation (consisting primarily of natural gas-based combined cycle units); intermittent generation (consisting of renewables like wind and solar) and a peaking generation (consisting of fuel oil and natural gas-based CT units). Due to the stochastic nature of renewable generation, the LDC for the rest of the dispatchable technologies can vary between

[49] The price suppression and intermittency effects are explained with the help of a LDC in this section (adapted from Miera et al. (2008)). These concepts are well documented in the literature and is usually analyzed using price vs. quantity curves (see Jensen and Skytte (2003) and Felder (2011) for examples).

the two specified LDCs (see Figure 6.8 Panel (a) & (b)). The incremental cost curves for each of the three generation technology types (i.e. the base-load, intermediate and peaking types) are plotted in Figure 6.7. The incremental cost curves are assumed to be linear and representative of each category of power plants i.e. all power plants within each category are assumed to have the same marginal costs. The intersection of incremental cost curves determines the number of hours in year in which the operation of each generation technology type is optimal. The length of the line segments in Figure 6.8 Panel (c)-(d) corresponds to the number of hours at which a given generating technology type sets the marginal system price. The annual wholesale ratepayers' cost of electricity corresponds to the product of marginal price in every hour within a given year and the magnitude of system demand in those corresponding hours. From Figure 6.8, we can infer that the effect of increased renewable power generation is a decrease in peaking unit generation and an increase in base-load generation. This reduces the average wholesale marginal price for the region, resulting in a price suppression effect. But this effect is unlikely to last on a long-term basis. Eventually, the intermittency in renewable generation and growth in system demand level is likely to result in increased generation from peak and intermediate units. Also, most of the base-load units in the PJM region are large coal and nuclear that are likely to retire in the coming decades. Based on the results from LP-CEM simulations, it is likely that these base-load units are going to be replaced by intermediate combined cycle units. These units are also better positioned to respond to the variations in dispatch requirements. This could potentially lead to an increase in dispatch costs. Optimizing the overall supply costs under these counteracting cost effects is likely to emerge as a key challenge for system operators like PJM in the future.

**Figure 6.6: Hypothetical LDC for a region with and without intermittent renewable generation**

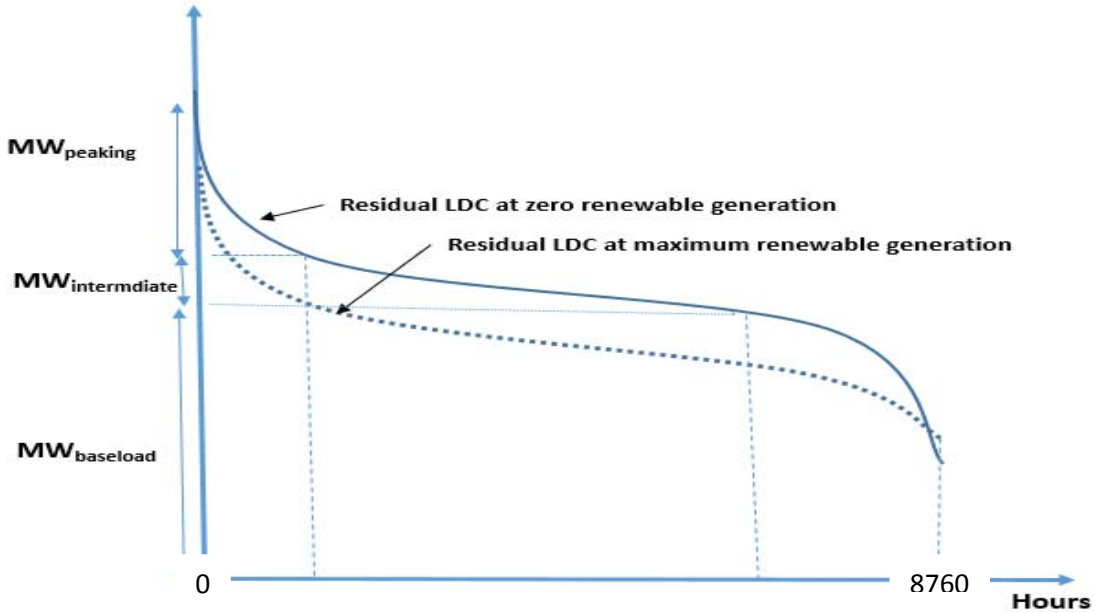



**Figure 6.7: Typical incremental cost curves for base-load, intermediate and peak generating units**

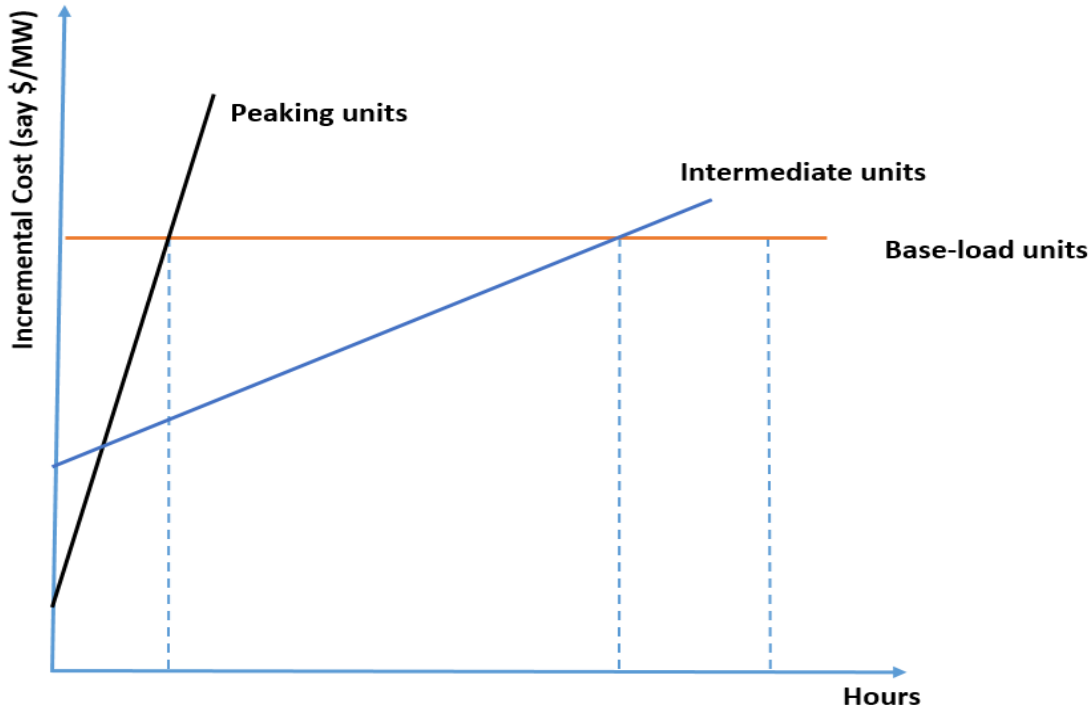
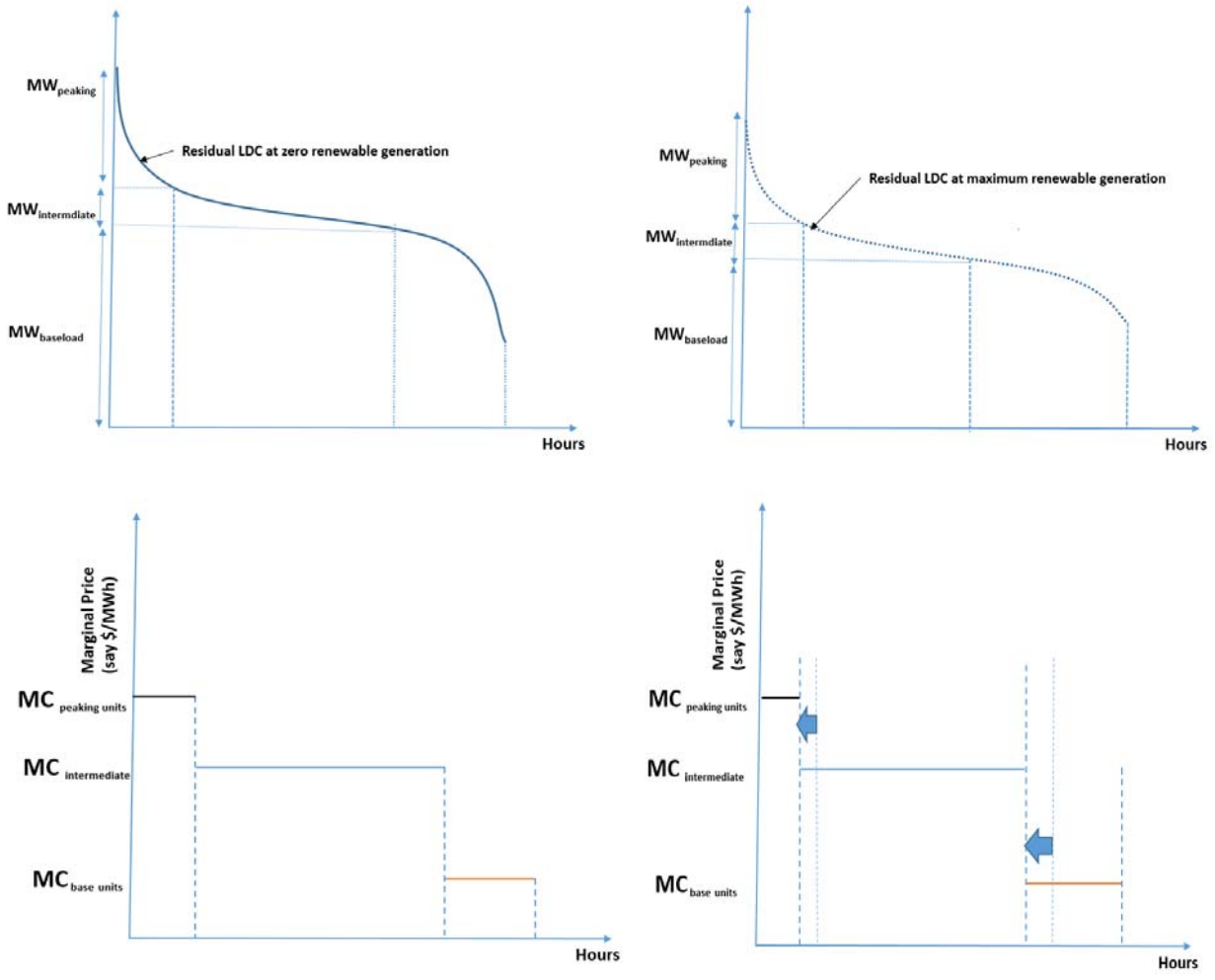


**Figure 6.8 (a)-(d) (starting from top-left to bottom-right) Implications of renewable intermittency on dispatch and wholesale prices**




### ii. Capacity Markets

The objective of PJM's capacity market is to provide an additional revenue stream for generators to compensate for their fixed costs. The capacity market arrangement involves a payment from load serving entities (LSEs) to generators for ensuring availability of capacity resources to meet the projected future demand. The LSEs in turn recover the cost of participating in capacity markets from final ratepayers. The Reliability Pricing Model (RPM) of PJM is a forward looking, annual, locational market, with compulsory capacity obligations for existing LSEs (Monitoring Analytics, 2011). A generator's capacity revenue is

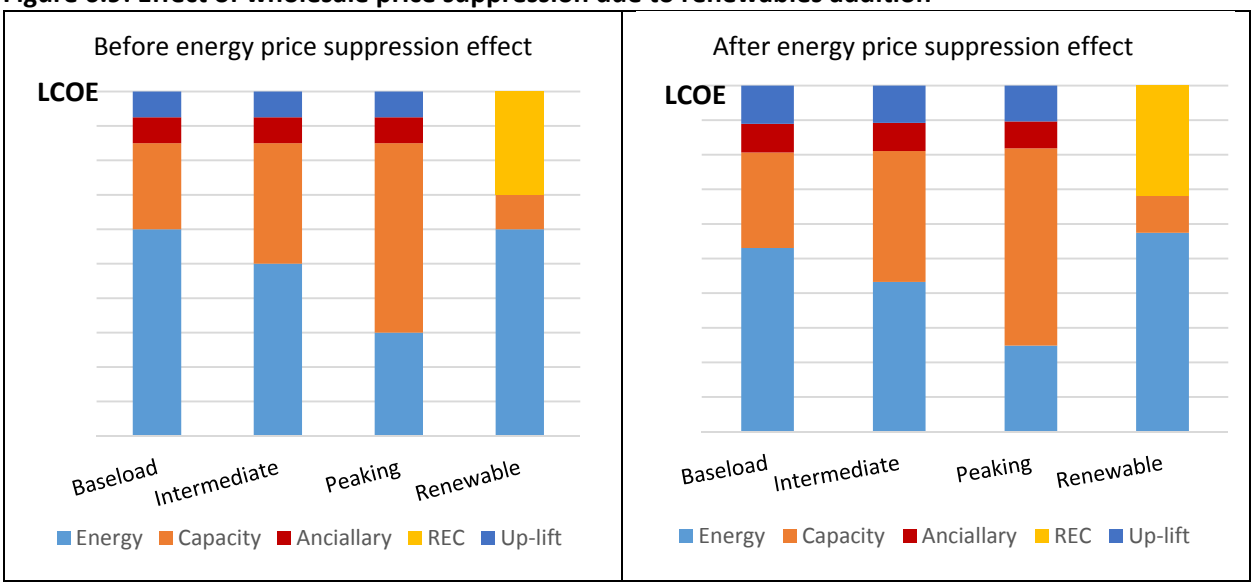
contingent on its capacity bid clearing the PJM RPM Base Residual Auction (BRA) or one of the subsequent Incremental Auctions (IA). For units that clear the capacity auction, the capacity revenue is given by the product of the following terms: (1) The unit's equivalent availability capacity (usually one for fossil fuel units); (2) One minus the unit's forced outage rate; (3) capacity price expressed in $/MW-day; and (4) Number of days in a year or quarter (Sotkiewiez, 2012). On average, the capacity payments for generators constitutes around 15-20% of the final PJM wholesale price (Monitoring Analytics, 2011. p.10). Lower energy prices (i.e. LMP) in the spot markets due to widespread renewables deployment is likely to reduce the energy revenues for conventional generators. A PJM study estimates that a 15,000 MW of on-shore wind capacity addition in the PJM region would result in an average reduction in LMP by up to $5/MWh (PJM, 2009). This would result in a lower energy market revenue for conventional fossil fuel generators. These generators must be compensated through a higher capacity prices in the RPM market in order to avoid the risk of premature retirements. One possible benchmark to compare the adequacy of capacity market revenue could be that of the net Cost of New Entry (CONE) for a simple combustion turbine (Sotkiewicz, 2012)[50]. Old fossil fuel units with a going-forward capacity revenue requirement exceeding the market CONE runs a high risk of retirement. Also, due to intermittent nature of renewable generation, the renewable capacity resources in PJM are assigned an equivalent capacity value at a fraction of their nameplate capacity[51]. Dispatchable technologies are assigned a high availability factor and consequently they are entitled to a greater share of capacity market revenues. System operators (like PJM) are likely to introduce capacity market design changes to ensure that the conventional fossil-fueled resources are adequately compensated and remain financially viable in the future.

[50] CONE denotes the annual net revenue (net of variable operating costs) that a new generation resource would need in order to recover the capital investments and fixed costs, under reasonable expectations of future cost recovery over its entire economic life. It is expressed in $/MW-year.

[51] For the LP-CEM model runs, the equivalent capacity value is assigned to be 0.2 and 0.3 for solar and wind respectively.

The price suppression effect and the need for increased capacity payments for fossil fuel generators is graphically represented in Figure 6.9. There are four possible revenue streams for a generator resource in a liberalized market like PJM. They include: energy market revenue, capacity market revenue, ancillary services payment, RECs for renewables and uplift charge (if applicable)[52]. For a generation unit to *not* operate at a loss, the unit generation cost must equal or exceed the levelized cost of power generation (LCOE) (under the given set of assumptions). Also, the ancillary payments are demand driven and cannot be counted as steady revenue stream in the long-run. Likewise, the uplift charges are determined out-of-market and are generally mitigated as much as possible by the market regulator in the interest of transparency and competition. Only a market-driven capacity payment can meet the shortfall in energy revenue. Large-scale renewables addition causes a suppression of the energy component of the wholesale price across all technologies. The effect of a 20% reduction in wholesale energy price is shown in the right panel of Figure 6.9. In a competitive capacity market, the increase in capacity payment is capped by the market CONE of new power plants. Hence existing power plants are placed at a clear disadvantage if their future capacity revenue requirement exceeds the market CONE.

**Figure 6.9: Effect of wholesale price suppression due to renewables addition**




[52] Up-lift charge is an out-of-market payment for a generator whose commitment and dispatch by the RTO/ISO results in a revenue shortfall for that generator. This is primarily caused by unanticipated system constraints.

The other major aspect of capacity adequacy is that of transmission resources. The current LP-CEM framework does not factor in transmission expansion. In the future, this framework can be expanded by accounting for transmission expansion as well. A brief overview on the nature of transmission expansion in PJM market is presented in this paragraph. Transmission upgrades in PJM are financed on a social cost basis by means of a centralized regulatory intervention (Monitoring Analytics, 2011). Even in a perfectly competitive wholesale markets, transmission investment decisions cannot be left to the discretion of the market participants alone (see Hogan, 2009). This is due to the natural monopolistic nature of the dispatching electricity through the grid and the public good nature of the benefits of such investments. Identifying the beneficiaries to bear the cost of transmission investments is also problematic considering the fact that once congestion is relieved, the benefits accrue not just to the parties that paid the cost but to all others in the grid. Also, in the short run it is against the generators' self-interest to reduce congestion prices, as it affects their revenues. However, it should be noted that not all transmission investments in the PJM network are currently socialized. A new generating unit or merchant transmission projects in the PJM network is responsible for the full cost of transmission linkage (Joskow, 2004). PJM's hybrid system of market-based and regulation driven investments is likely to continue in the future as well (see Hogan, 2010).

#### iii. Ancillary Services Market

FERC has identified and defined six major ancillary services for ISOs/RTOs. (Monitoring Analytics, 2011). They include: scheduling, system control and dispatch; reactive supply and voltage control from generation service; regulation and frequency response service; energy imbalance service; operating system reserves – synchronized reserve and supplemental reserve service. PJM addresses regulation and operating reserves requirements by means of a dedicated regulation market (Monitoring Analytics, 2011). Generator firms bid for offering regulation services for the following day. The bids are valid for the entire day. Generator firms that are used for regulation services are then paid a unit specific-opportunity cost

corresponding to the forecasted LMPs plus their offer bid amount. Energy imbalance services are rendered by real time (RT) energy markets. Other ancillary services like reactive supply and black-start services are administered through regulatory interventions.

The intermittent nature of renewable resources is likely to increase the Day-ahead Scheduling Reserve (DASR) margin for PJM markets. At present this margin is around 15-20% for U.S based RTOs/ISOs (Joskow, 2006). For a future system with intermittent renewable penetration of 20% or higher, this margin will be insufficient. In the absence of effective storage technologies, the intermittency problem could in fact result in an increase in system-wide start-up costs and operating reserves costs. For the PJM market, there is a supplementary reserve that can come online in no less than 30 minutes and a synchronized reserve that can come online in no less than 10 minutes (PJM Operating Reserve, 2012). It is possible that an additional class of operating reserve with a 5-minute interval could be instituted in the future to meet the intermittency in supply or demand (cf. Joskow (2006) who suggests a similar idea in the context of "missing money" problem). For the current set of LP-CEM runs, a unified reserve margin of 15-16% is specified for each sub-region based on system operators' data (summarized in EIPC, 2013). For future modeling efforts, the LP-CEM framework can account for renewable intermittency issues by specifying an increased reserve margin.

#### iv. Other institutional aspects

While so far the discussion has centered on three major institutional markets of PJM, there are other aspects of the market that are likely to get affected by climate change policies. Market power is one such major problem that is likely to plague any wholesale market of the future. Market power is said to be exercised by a firm if it reduces its output or increase its price to *manipulate* the market clearing price. Ideally in perfectly competitive markets, no firm can afford to exercise market power for there would be other competitive firms to supply the reduction in quantity or offer lower prices. Also, if one firm gets to exercise market power, the benefits generally accrue to all firms in the market on the account of increased

clearing price (Borenstein, 2000). Unilateral exercise of market power *per se* is not illegal. It is only the exercise of market power by a group of *colluding* firms that is against the law (ibid.). The ability of a firm or a group of firms to exercise market power is correlated to a great extent to its market share. PJM currently employs a three pivotal supplier (TPS) test to check the competitive conditions in its various wholesale markets. It tests the degree to which the output (generation in energy market and capacity in capacity markets) from the three pivotal suppliers is required to meet the demand or to relieve a constraint (PJM-TPS, 2007). TPS tests are better structured to detect market power in comparison to the conventional tests involving Herfindahl index or Lerner index. The current version of LP-CEM operates on a marginal cost basis without accounting for market power or strategic behavior of *individual* market participants. In the future it is possible to develop a multi-objective equilibrium framework for the power sector incorporating non-competitive tendencies of market participants.

Based on the observations outlined so far, it is possible to predict the course of action that PJM or any other system operator is likely to execute in the future to mitigate market power. Two aspects of market power are essential for firms to earn excess profits. First, market power depends on the sensitivity of system demand or supply to a price increase/quantity decrease by one firm or a group of firms. Second, it also depends on the ease with which new firms can enter the market. With demand response and a flexible operating reserve, it becomes difficult for firms to unilaterally influence the market price. In markets with little barriers for new firms to enter, the exercise of market power by existing firms is unlikely to continue for a prolonged period of time. However, policy interventions in a carbon-constrained future (like RPS, carbon caps and $SO_2$- NOx rules) in effect imposes regulatory barriers for firms (like new coal units) to enter the market. From PJM's perspective, a fragmented supplier base is in the interest of market efficiency. The benefits from a fragmented supplier base must be balanced with the benefits that come from the economies of scale in generation.

Also, regulations at both the Federal and state-level affect transactions in PJM markets. Generators in the PJM market are subject to EPA's regulations like Acid Rain program, Mercury and Air Toxics Standards (MATS) and Clean Power Plan Rules (Section 111(d)). These regulations necessitate expensive retrofits for older fossil fuel plants using coal or natural gas. If the revenues from the RPM capacity market fail to compensate for these retrofit costs, there is a high risk of premature retirement of these units. A PJM study carried out in 2011 estimates that nearly 11,000 MW of coal units are at risk of retirements due to MATS and then proposed Clean Air Interstate Rules (CAIR) (PJM, 2011). With the current set of Clean Power Plan rules and MATS, about 60,000 MW of coal capacity is at risk for retirement for the whole of United States[53].State-level regulations, like RPS and RGGI, are currently applicable to the corresponding LSEs in various PJM jurisdictions. The emissions regulations target the generators that emit the pollutants. The renewable obligations target the supplier at the distribution end. The ISOs/RTOs in the transmission sector are presently not subject to any type of major Federal or state regulations (except for reliability standards).

## 6.5 Sectional summary

The electric power sector of the future is most likely to operate in a carbon-constrained environment. Coupled with the demand and supply-side transformations like distributed generation, demand response and energy efficiency, the future of electric power sector presents a host of opportunities and challenges for system operators and regulators. The current economic and regulatory policy environment calls for capacity market design changes to ensure the financial viability of fossil fuel units. There is a need to *expand* this *scoping study* to analyze the future implications for wholesale market design in a more systematic and comprehensive manner.

[53] ICF International- http://www.icfi.com/news/2014/10/icforecast-energy-outlook-regulatory-complexities-and-natural-gas-economics-driving-power-markets

## 6.6 Impact of extreme events on the electric power distribution network

Hurricane Sandy was a wake-up call for institutions and policymakers to the vulnerabilities of the electric power distribution to climate change and extreme events. Extreme weather events are the leading cause of power outages in the United States (Hoffman and Stock, 2013; DOE, 2013). These extreme events include an extreme warm/cold temperatures, extreme high sea levels and high precipitation events (IPCC, 2013). The current version of LP-CEM does not incorporate the impact pathways of extreme events on the electric power sector. Also, the scope of LP-CEM was restricted to the wholesale aspect of the power sector, without considering the impacts at the distribution end. Nevertheless it remains an important topic for future modeling work (also see Section 3.3). Impact assessment research can benefit from a better understanding of climate dynamics especially that of precipitation patterns and ocean surface temperature projections[54]. From a modeling framework perspective, it is possible to incorporate the effects of extreme events through a stochastic specification of the average damage costs in the objective function. Another option is to run a robust optimization version of the LP-CEM with different probability weights attached to various climate-economy impact scenarios. Investments in grid modernization and resilience will help to mitigate the overall damage costs over time. An expansion framework like LP-CEM would help to plan for a capacity portfolio that is robust and resilient to uncertainty in future climate projections.

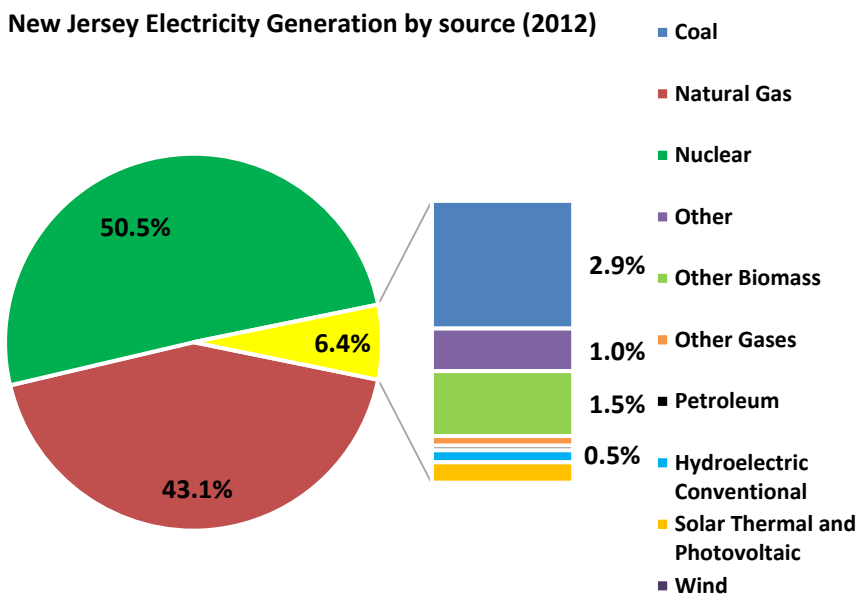
This section presents an assessment of the impact of Hurricane Sandy on the electric power sector in the NYC-NJ region with the objective of informing forward-looking planning measures. These measures usually take the form of adaptation and mitigation strategies implemented by public institutions (i.e. the Federal, state and local governments and regulatory entities) and private institutions (i.e. utilities, generators and end consumers) related to the electric power sector. A brief overview of the key electric

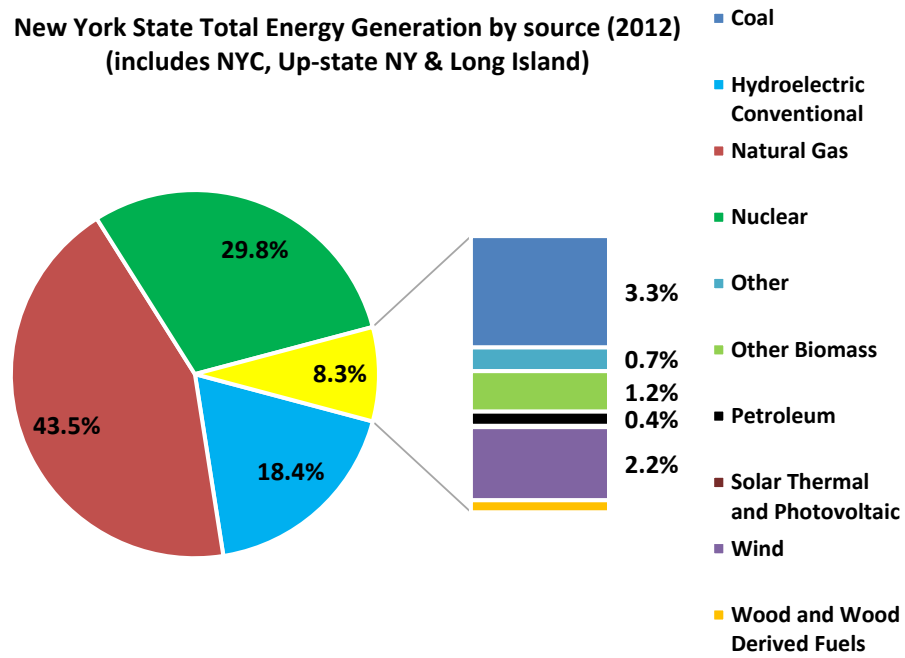
[54] Hurricane intensities are predicted to be dependent on the temperature difference between surface ocean and mid-level atmosphere. In a warming scenario, this difference is expected be more pronounced thereby resulting in increased hurricane intensities in the future (see Kossin et al., 2007; Hoffman and Stock, 2013).

power sector statistics for New Jersey and New York states is presented in Figure 6.10 for the reader's benefit. This section primarily reviews the challenges and institutional responses to Hurricane Sandy by regional/state-level stakeholders. A set of planning and policy recommendations are presented in the concluding section of this chapter for power sector stakeholders.

To better understand the challenges in planning and responding to future extreme events, it is critical to analyze the responses to past events like Hurricane Sandy. In addition to human costs, the storm caused an estimated economic damage of over $30 billion in NYC-NJ region alone (NOAA, 2013a; Mantell et al., 2013). There is a certain degree of consensus among the current long-term climate projections that the frequency and intensity of extreme events are likely to *increase* in the coming years (IPCC, 2013; Hoffman and Stock, 2013; DOE, 2013). In the U.S, the frequency of extreme events (the so-called "billion dollars event") has increased in the last thirty years (see Figure 6.11 for recent trends). The aggregate losses to the society have also increased manifold over the last few years. For the U.S, the year 2012 was the second most expensive year in terms of economic losses due to extreme weather events. The losses have been estimated at around $100 billion with Hurricane Sandy alone accounting for $65 billion (NOAA, 2013). Figure 6.12 highlights the increasing incidence of weather-related grid disruptions in the U.S. Weather-related outages account for nearly 60% of the outages observed since 2000 (based on DOE-Form OE-17 data). For the years 2002-2012, weather-related outages were estimated to cause a damage of $18-$33 billion annually (Hoffman and Stock, 2013). These costs ae incurred by the utilities in the form of repair and restoration services, and by consumers in the form of lost load and economic productivity.

**Figure 6.10: Comparison of key electricity statistics for New Jersey and New York**

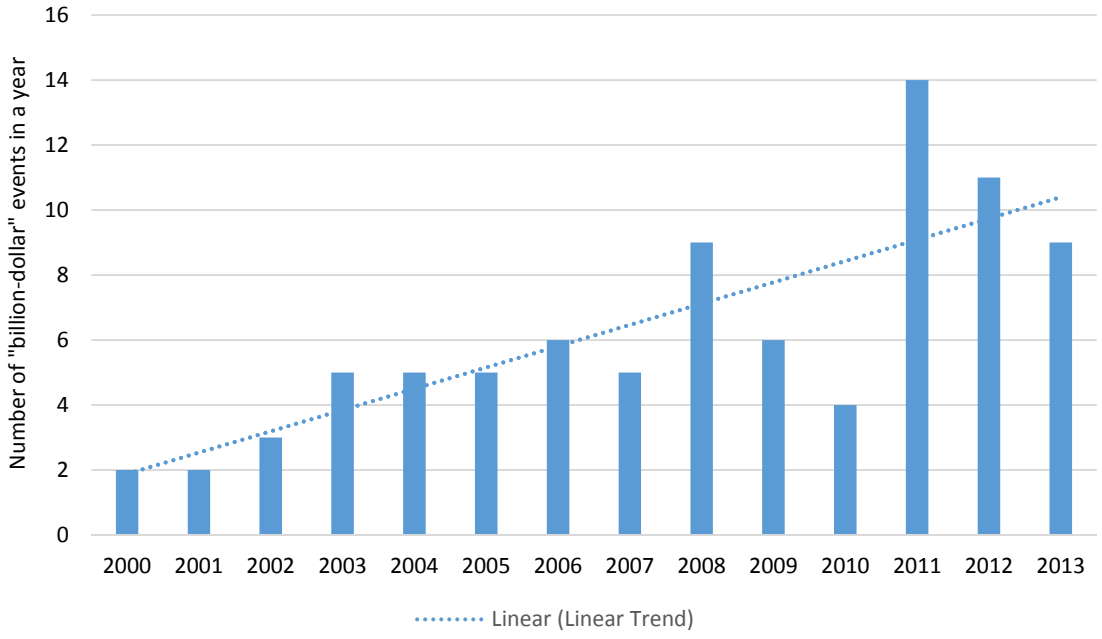



| | |
|---|---|
| Total Demand for Electricity in New Jersey in 2012 is **75, 053 GWh** | Total Demand for Electricity in New York State in 2012 is **143,163 GWh** |
| Total installed capacity (as of 2010) is **18,424 MW** (summer capacity) | Total installed capacity (as of 2010) is **39,357 MW** (summer capacity) |
| Average retail price of electricity in New Jersey (for 2012) is **13.68 cents/kWh**<br>Retail Prices by sector (for 2012):<br>Residential- 15.78 c/kWh; Commercial- 12.78 c/kWh; Industrial- 10.52 c/kWh | Average retail price of electricity in New York ( for 2012) is **15.15 cents/kWh**<br>Retail Prices by sector (for 2012):<br>Residential- 17.62 c/kWh; Commercial- 15.06 c/kWh; Industrial- 6.70 c/kWh |
| Number of retail customers in New Jersey is **3.95 million (approx.)**<br>Customer base split-up:<br>Residential- 87.3%, Commercial- 12.4%; Industrial- 0.3% | Number of retail customers in New York is **8 million (approx.)**<br>Customer base split-up:<br>Residential -85.5%, Commercial- 13.7 % , Industrial- 0.8% |
| Key Utilities:<br>**EDCs-** Jersey City Light and Power (JCP&L); Public Service Electric & Gas Company (PSE&G); Atlantic Electric (AEC) & Rockland Electric (REC)<br>**Generators-** PSEG Fossil; PSEG Nuclear**,** Morris Energy | Key Utilities (in NYC region alone):<br>**EDCs**- Consolidated Edison (Con Ed); Long Island Power Authority (LIPA)<br>**Generators** – New York Power Authority(NYPA), Con Edison Development |

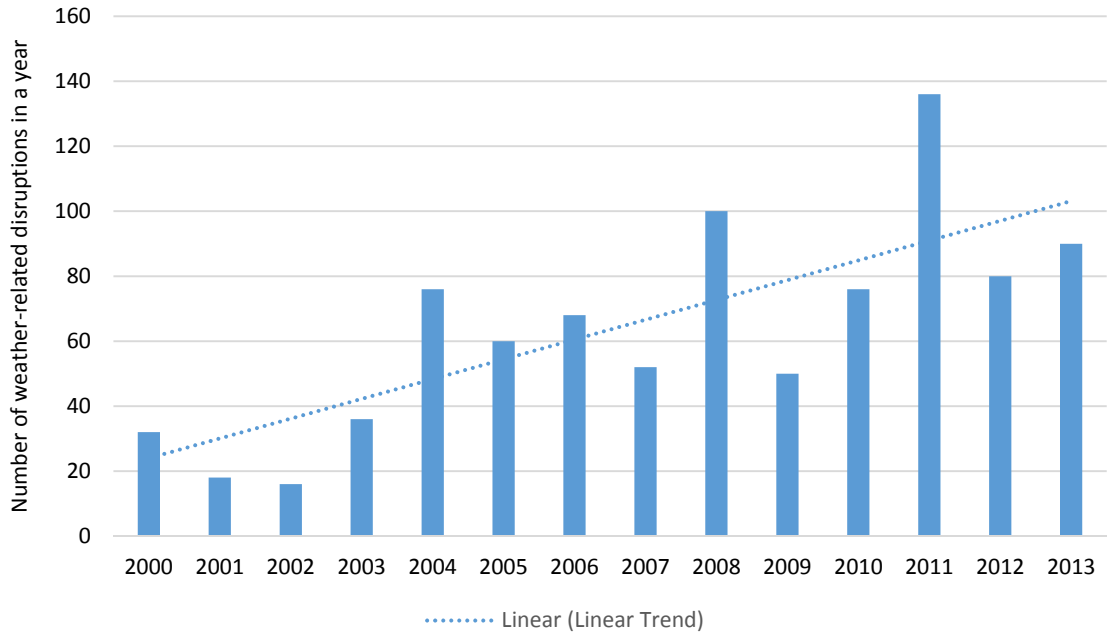
Source: US EIA (Form 860, 861, 923) for New Jersey & New York - http://www.eia.gov/electricity/data/state/

**Figure 6.11: Incidence of "billion-dollar" weather events in the U.S 2000-2013**




Source: NOAA (2013). Cost estimates of extreme event damages are inflation adjusted

**Figure 6.12: Weather-related disruptions of electric grid in the U.S 2000-2013**




Source: DOE- Office of Electricity Delivery & Energy Reliability (OE-17). http://www.oe.netl.doe.gov/oe417.aspx
Note: : Weather events include tropical storms, hurricanes, tornadoes, heat waves, wild fires, thunderstorms and other related events. The weather events are not weighted by magnitude or scope of impact.

## 6.7 Hurricane Sandy- A synoptic summary

A synopsis of Hurricane Sandy and its aftermath is presented in this section for the reader's benefit (based on Blake et al., 2013). Sandy was a post-tropical cyclone that hit New Jersey coast on October 29-30, 2012. At landfall, it was officially designated a Category 1 post-tropical storm with sustained wind speeds up to 80 mph (or 70 knots). Due to its tremendous size, it caused massive storm surges in New York City and New Jersey region. This was the second deadliest hurricane to hit the country (next only to Hurricane Katrina of 2005) with direct attributable deaths of around 159 people and economic damages of around $65 billion. The storm surge was the highest in New Jersey, New York City and Connecticut coastline, ranging from 3 feet to 9 feet above mean low tide level. Coastal inundations were also widespread in this region. As a result of this tropical storm, nearly 650,000 homes were destroyed and around 8.2 million retail customers lost power in the whole of U.S Northeast. Nearly 5 million of these customers were located in the New Jersey- New York city region alone. Figure 6.13 presents a timeline of power outages in the region due to Sandy and the immediate period of restoration. Even ten days after Hurricane Sandy made landfall nearly 700,000 customers in the Northeast region remained without power[55]. The damage to electric power infrastructure in the region was unprecedented. On the generation side, nearly 8,000 MW of generating capacity in NYISO area was affected due to flooding or damages to power evacuation lines from the plants[56]. Ten days after the storm, nearly 2,200 MW of generation was still unavailable for dispatch in NYISO region[17]. Storm surges in New York City area destroyed parts of the underground network of distribution systems. Flooded basements in New York City area resulted in the loss of back-up generator power for some hospitals and offices in Downtown area of the city[57]. The estimated losses reported by major utilities (mostly EDCs) are listed in Table 6.1. Utilities are likely to incur huge labor and

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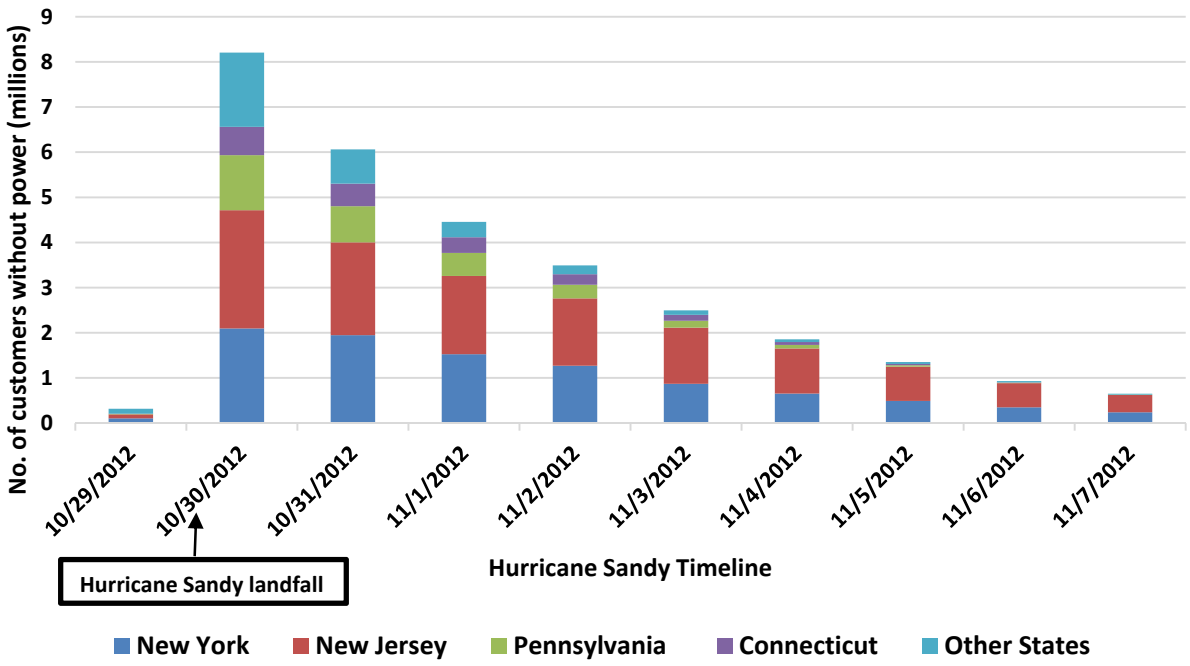
[55] U.S Energy Information Administration - http://www.eia.gov/todayinenergy/detail.cfm?id=8730

[56] NYISO. *Hurricane Sandy- A Report from New York Independent System Operator* - http://www.nysrc.org/pdf/MeetingMaterial/RCMSMeetingMaterial/RCMS%20Agenda%20158/Sandy%20Report%202-22-13%20Public%20Version%202.pdf

[57] Time magazine- http://healthland.time.com/2012/10/30/lessons-from-storm-sandy-when-hospital-generators-fail/

material costs to restore electric power. The expenses incurred by the utilities are likely to be recovered from the ratepayers in the coming years. A rough estimate of the cost incurred by the electric power sector in the NJ-NYC region alone is likely to touch $2 billion. This estimate does not include the costs incurred by residential customers, commercial business and industries due to power outages or other private damages to homes and properties.

**Figure 6.13: Hurricane Sandy power outages and restoration timeline**




Source: US-DOE: Office of Electricity Delivery and Energy Reliability. *Emergency Situation Reports-Hurricane Sandy*[58]

[58] U.S. DOE- http://www.oe.netl.doe.gov/named_event.aspx?ID=67

**Table 6. 1: Estimated cost of damage, repair and restoration of utility assets in NYC-NJ Region[59]:**

| Utility (State) | Estimated cost of recovery |
|---|---|
| Jersey Central Power and Lights (JCP&L) (a subsidiary of First Energy Inc.) (New Jersey- North & South) | $680 million |
| Public Service Electric and Gas (PSE&G) (New Jersey-Central region) | $420 million |
| Consolidated Edison (Con Ed) (New York City) | $521 million |
| Long Island Power Authority(LIPA) (New York- Long Island) | $800 million |

Note: Cost estimates are based on publicly available press releases and articles. The cost estimates also includes the repair and restoration of gas services in the region.

## 6.8 Immediate responses to Hurricane Sandy by power sector stakeholders

This section summarizes the short-term responses to Sandy from important stakeholders like utilities, regulators, the Federal and state governments (DOE, 2013). The Federal government, in close co-ordination with Federal Emergency Management Agency (FEMA), deployed "Assessment Teams" on the ground at various states in the Northeast to monitor and address the problems caused by the storm. The Obama administration also waived the requirement of proportional State government funding for relief efforts, thereby increasing the Federal component of relief money substantially. The Department of Energy (DOE) engaged in daily co-ordination calls with operational heads/CEOs of utility companies to assess their needs and to prioritize restoration efforts. On an unprecedented scale, nearly 67,000 utility personnel from over 80 electric utilities across United States participated in the immediate repair and relief effort (under a program of "mutual assistance personnel")[20]. Within two weeks after Sandy's landfall, power was restored to nearly 99% of the customers who lost power. The DOE also published periodic situation reports to update on the status of repair and restoration services (see source in Figure

[59] LIPA- http://www.lipower.org/newscenter/pr/2012/111912-update.html ;
PSEG- http://www.law360.com/articles/454461/nj-utility-co-battles-insurers-over-sandy-recovery ;
Con Ed- http://www.forbes.com/sites/williampentland/2013/05/09/superstorm-sandy-was-super-expensive-for-con-edison/ ;
JCPL- https://www.firstenergycorp.com/content/fecorp/newsroom/news_releases/jersey-central-power---light-submits-rate-filing-for-hurricane-s.html

6.3). One key challenge that was observed during the storm was the interdependency of oil and gas sector (O&G) on the electric power sector. The storm caused major disruptions to O&G sector by affecting refining and pipeline distribution operations on the NYC-NJ coast. There were also widespread gasoline shortages due to power outages at retail gas stations. Thus a combination of damages to ports and refineries; widespread power outages and high demand for gasoline fuel led to gas rationing policies in NY-NJ region in the immediate aftermath of the storm.

Apart from repair and restoration efforts, the utilities and regulators subsequently embarked on various "hardening" measures to improve the resiliency of the electric power sector. The "hardening" measures can be roughly classified under two types: tangible and soft types (see Table 6.2).Vegetation management issues (i.e. trimming the tree branches overhanging or growing near power lines) are a low-cost remedy to mitigate damages caused to distribution power lines and transmission poles in the event of an extreme event like Hurricane Sandy. In the aftermath of Sandy, PSE&G, the utility-based in New Jersey, removed or trimmed nearly 48,000 trees to restore power (Blake et al., 2013). The other key "hardening" measure involves increasing the grade height of sub-stations, transformers and other key installations, to protect them from storm surges. Utilities are also leveraging on Advanced Metering Infrastructure (AMI) to facilitate power restoration and improve communications with end consumers. AMI helps in tracking the location of power outages and helps utilities to respond faster. One other "hardening" measure is the deployment of automatic switches/SCADA[60] systems that can control vulnerable distributions equipment from a central location. These systems help to minimize the damages to the electric power grid and also help in efficient power restoration. Apart from these tangible "hardening" measures, there are other soft responses like better emergency co-ordination in repair and restoration works; a more resilient information and communication (ICT) infrastructure; and better emergency response planning. In

[60] SCADA- Supervisory control and data acquisition

addition, there are private adaptations on the part of individuals that can contribute to the overall grid resiliency (see Table 6.2).

**Table 6.2: Major "hardening" responses by select stakeholders connected to electric power sector**

| Stakeholders | Tangible "hardening" measures | Soft "hardening" measures |
|---|---|---|
| **Individual customers** | Private generator backup, placement of back-up generators on higher floors | Better disaster preparedness |
| **Utilities** | Vegetation management | Better co-ordination in repair and restoration works |
| | Raising/relocating substations and transformers | Better communication protocol to handle crisis situations |
| | Deployment of Automatic switching/SCADA systems, ICT infrastructure | Co-ordination with out-of-state utilities personnel |
| | Flood water barriers to power installations | |
| | Deployment of AMI | |

## 6.9 Planning and policy recommendations for future challenges of climate change and extreme events

There is overwhelming evidence pointing to the fact that extreme weather events like Hurricane Sandy are likely to inflict greater economic damages in the future. As this chapter pointed out, the disruption to power supply can have crippling effects on the economy and on our societal well-being. A multi-pronged approach is required to develop a more resilient power sector with capabilities to handle climatic shocks. I have outlined some of the key planning and policy recommendations for the power sector stakeholders in this section (also see DOE (2013) for a list of similar recommendations).

*a. Invest in grid hardening*

As mentioned earlier, the various "hardening" measures would considerably improve the power grid's capacity to withstand climatic shocks. Utilities should prioritize investments on low-key and local "hardening" measures like vegetation management, distribution and transmission line strengthening, and protection of power assets from storm surges and flooding.

*b. Invest in emerging information and communications infrastructure (ICT)*

Utilities and system operators should also focus on deploying cyber infrastructure technologies[61] like SCADA, Advanced Metering Infrastructure (AMI), Outage Management Systems (OMS) and Distribution Management Systems (DMS). These technologies contribute to a better situational awareness of the grid and a more efficient response to power outages.

*c. Regulators must consider the costs and benefits of grid modernization investments*

State BPUs and system operators must consider the long-term societal benefits of hardening and modernization investments incurred by utilities. These investments are likely to be recovered from ratepayers in the form of a socialized "rate-base". Any cost-benefit analysis by the regulators must also take into account the fact that incidence of extreme events are likely to increase in the coming years and such shocks can inflict enormous cost on the society.

*d. Develop weather/climate projections model that can accurately identify key vulnerabilities*

Electric utilities and system operators must closely work with climate science community to develop accurate short-term weather projections models and perhaps long-term climate models with emphasis on predicting the potential damages to electric power assets. This would translate into incorporating weather-related phenomena like hurricanes, storm surges and flooding patterns, into impact assessment and vulnerability models for the electric power sector.

*e. Standardize the procedures for the "mutual assistance" programs for utilities*

Mutual assistance responses are vital in responding to widespread disruptions caused by climatic shocks. Electric utilities across the country must collaborate to develop a set of interoperability guidelines for integrating out-of-state personnel and resources in grid repair and restoration works.

[61] For a description of these technologies see the Glossary section at: https://smartgrid.gov/

*f. Co-ordinate the emergency response planning process across different tiers of stakeholders*

The scale of Sandy's destruction necessitated direct co-ordination among decision makers at utility companies and the Federal government. These communications helped to coordinate the repair and restoration efforts across the region and also provided situational awareness on the scale of destruction to the Federal government. There is a need to standardize these vertical communication channels and develop communication protocols to better handle the emergency response.

*g. Identify the interdependencies of oil and gas(O&G) sector with electric power sector and develop appropriate response plans for O&G sector as well*

Sandy exposed the interdependencies between the O&G sector and the electric power sector. It also highlighted the need to implement a coordinated response plan on a regional/national scale for the O&G sector by the Federal and state governments. The O&G sector could also explore the possibility of establishing a "mutual assistance" program along the lines of the existing initiative in the electric power sector.

*h. Acknowledge the tradeoff between investing in mitigation and adaptation efforts*

Finally, society must also acknowledge the tradeoff in investing in mitigation efforts vis-à-vis adaptation efforts. To a certain extent, mitigation efforts, such as distributed renewable generation, micro-grids and demand response, helps to minimize the damage caused to the environment and also reduces the vulnerability to physical damages from extreme events.

## 6.10 Sectional summary

Extreme storm events, like Sandy, have highlighted the infrastructural vulnerabilities and also the institutional shortcomings in responding to such events. The current modeling framework can be enhanced through a better understanding of the underlying geophysical processes behind each of the

extreme events and the associated impact pathways on the various socio-economic systems. In the near term, LP-CEM-like model framework can be improved through a stochastic specification of damage cost function. The various grid modernization technologies and “hardening” measures highlighted in this chapter have the potential to reduce power outages in the future. The institutional reforms outlined in this chapter can ensure a faster recovery from climatic shocks in the future. Utilities, regulators, Federal/state governments and ratepayers must work collaboratively towards implementing these recommendations for a more resilient power sector of the future.

# Chapter 7

# Conclusion

## 7.1 Future Challenges

Today's electric power sector faces complex economic, environmental, market, and regulatory challenges when dealing with climate change and its impacts. These challenges include: mitigating the GHG emissions from fossil fuel units; investing in appropriate clean energy technologies that can meet the future changes in demand; implementing demand and supply-side flexibilities, like demand management and distributed generation, without compromising the supply reliability; ensuring a resilient power infrastructure to extreme events and climate change; gearing up to meet the potential implications from electrification of the transportation sector; implementing market reforms and other governance adaptations to address the emerging issues with the power sector; mitigating other adverse pollutants like mercury and particulate matter; and ultimately ensuring a clean, reliable and cost-effective electric power to end consumers.

Achieving a "deep reduction" in GHG emissions of 80% or more requires a portfolio of mitigation and adaptation efforts targeting not just the electric power sector but the entire economy. A model like LP-CEM could play an important role in formulating the electric power sector's strategy to this "deep reduction" commitment. As the LP-CEM simulation runs in this dissertation research demonstrate, it is possible to achieve a "deep reduction" in emissions without significant costs to the broader economy. Addressing these climate change effects through abatement measures like RPS and $CO_2$ emissions caps are likely to cost roughly *0.45%* annual GDP measure for the Northeast region[62]. Although the absolute

[62] This estimate was computed as follows: The average demand for the Northeast region was assumed to be 600 TWh (for each year) from 2010-50. The average wholesale cost was assumed to be $ 55/ MWh (all based on LP-CEM inputs and results). The annual total energy cost is around $ 33 billion. The average LCOE for carbon-free electricity like nuclear and renewables is roughly 40% higher (see EIA-AEO, 2014). Hence the annual energy costs in a low carbon economy would be around $46.2 billion. The regional GDP for the Northeast is approximately $2.9 trillion (20% of national GDP of $14.5 trillion). Hence the additional amount spent for a low-carbon generation is 0.45% of GDP for each year ( i.e. 13.2 billion/2.9 trillion= 0.0045)

cost of a transition to a low-carbon generation portfolio is considerable, it is certainly manageable. These costs are comparable to the EPA's Acid Rain program to limit the emissions of NOx and $SO_2$[63]. The long-run public health and environmental benefits of such mitigation measures greatly outweigh the costs (see EPA-RIA, 2014). The path to a low-carbon economy calls for clear regulatory mandates and policies. The proposed Clean Power Plan (EPA's Section 111(d) rules for existing plants) is a step in the right direction. The Clean Power Plan, when implemented in full measure, will reduce the overall emissions from the power sector by 30% by 2030 (as compared to 2005) (EPA-RIA, 2014; Littell and Speakes-Backman, 2014). This chapter summarizes some of the key findings from R/ECON-LPCEM simulation runs and also furnishes a set of policy recommendations for the electric power sector to contribute to this economy-wide response to climate change. The limitations of this dissertation research and future research directions are presented in the final section of this chapter.

## 7.2 Significant findings from this dissertation research

- Climate change has profound implications for the electricity sector, especially for the future of electricity demand and supply. Increasing temperatures, decreasing freshwater availability, increased incidence of extreme storm events and periodic coastal flooding are expected to affect the ability to generate, transmit and distribute electrical energy to end consumers.
- In spite of the widespread effects of climate change on the electric power sector, the understanding of impact pathways of various climate parameters is not clear and comprehensive. The impact pathway of surface temperature is well explored in the literature. The impact pathways of other climate variables - like precipitation, solar radiation, ocean surface temperature and wind speed, are not well modeled or analyzed in the power sector assessment literature.

[63] EPA estimates the benefits-to-cost ratio of Acid Rain cap-and-trade program at 40-to-1 in 2010. See: http://www.epa.gov/capandtrade/documents/benefits.pdf

- The knowledge frontier has advanced on certain aspects of power sector impact assessment like: the effect of temperature increase on system demand and thermal power generation (for prototypical plants), the impact of cooling water availability on thermal power generation, the effect of precipitation and changes in river flow on hydro-power production, and localized impact of wind speed on wind power output.
- The research areas where the impacts remain unclear include: system-wide impact on renewable and thermal power generation; modeling the physical and economic effects of extreme events, vulnerabilities of energy infrastructure to extreme events (like transmission network, distribution lines and power plants), realistic integration of demand and supply-side effects at a state or regional level, the implications for electricity market design, and the effects of climate and policy uncertainty on modeling outcomes.
- Recent advancements in climate data availability give a fresh impetus for modeling and analyzing climate change impacts on the power sector. A list of open-source climate datasets and projects presented in Table 3.1 can help policymakers and model developers of the electric power sector.
- This research demonstrates the feasibility of incorporating climate change effects and macroeconomic trends into a GEM/CEM framework. Such models are of use to state/regional level policymakers related to the electric power sector to plan for future mitigation and adaptation measures to climate change and variability.
- Scenarios with climate variability, climate change effects and high economic growth have consistently resulted in higher capacity addition (in MW), supply costs, prices and ratepayers' costs. The bulk of the capacity addition is expected to be advanced combined cycle units for the Northeast region. These units can supply to both the intermediate and peak system demand. Nuclear and on-shore wind additions are also likely to be substantial in the coming decades for Northeast region.

- The growth rate for wholesale price projections, under all climate change scenarios, corresponds closely to the fuel cost escalation rate for natural gas (at 2.1% a year). This is due to the fact that natural gas units are expected set the marginal wholesale price at most time periods in the future (in a competitive market framework). This result is also dependent on the fuel price spread between coal and natural gas. Hence future wholesale electricity prices are expected to be strongly correlated with natural gas prices.

- For the years 2013-2040, the increase in average annual retail prices for New Jersey is expected to be around 0.08-0.11 cents/kWh (2012) assuming the climate change and variability effects on the wholesale price component alone. The final effect on the retail prices is most likely to be higher if the effect of climate change and variability on dispatch, distribution, ancillary services, regulatory costs, and grid reliability are also factored in.

- Over the years 2013-2040, the NPV increase in retail ratepayers' costs is expected to range from $1.9 to $4.3 billion under different scenario themes (all terms in 2012 $). This increased energy cost is likely to have ripple effects on the wider macro-economy of New Jersey. This ratepayer cost increase is computed with reference to a baseline R/ECON projection.

- A combination of a RPS policy and an emissions cap does not lead to a substantial increase in wholesale prices. On average, wholesale prices are expected to increase by 3-8% for scenarios with $CO_2$ emissions cap under the proposed Clean Power Plan rules. The average price increase is comparatively lower for scenarios with higher RPS mandates (i.e. *Option2* pathway of Clean Power Plan). This is primarily due to two factors: the price suppression effect caused by renewable generation and the less stringent $CO_2$ emissions reduction targets.

- Overall supply costs are lower for scenarios employing an *Option2* deployment of emissions target (Chapter 5). This can be attributed to two factors. First, an *Option2* pathway has a lower $CO_2$

emissions reduction target. Second, higher renewable addition results in lower generation costs. It should be noted that the current set of model runs does not factor in the intermittent nature of renewable generation. Also, the total price of electricity is lower in an *Option2* pathway as compared to an *Option1* pathway.

- For the current set of model assumptions, nuclear power generation is critical in meeting the carbon caps for the Northeast region. The power generated from nuclear power plants supplies nearly 40% of the total demand in the Northeast region for the various simulation runs. From an LP-CEM perspective, emissions-free power generation from baseload nuclear power plants is the most cost effective way to comply with the emissions cap imposed by the proposed Clean Power Plan rules.

- RPS-type instruments and carbon caps are cost effective in encouraging greater renewables generation. Carbon caps are the most cost-effective way to reduce $CO_2$ emissions from the power sector. This is based on the marginal abatement cost metrics derived for the RPS-only and Emissions cap-only scenario themes (see Figure 5.6 and 5.7).

- The maximum cumulative $CO_2$ emissions level for the Northeast region is 7601 MT $CO_2$ for the years 2010-50 and the minimum cumulative renewables generation for the corresponding period is equal to 4693 TWh. These policy targets correspond to the polynomial fit for the abatement cost curves. There is a need to calibrate the RPS and emissions cap instrument design for the region with these target bounds under consideration.

- The co-implementation of RPS and carbon cap policy is likely to benefit the Northeast region in the long-term. From the model runs, the interaction of RPS and carbon cap policy is expected to increase the wholesale prices by 3-8% and retail prices by 20-30% in 2040. The retail prices in this context incorporates the unit cost of implementing the policy programs. There are also other co-

benefits to these policies like improvements in air quality, public health outcomes, fostering renewable energy innovation, boosting economic growth, and grid resiliency. These benefits are more than likely to make up for any potential increase in supply costs due to the implementation of the emissions cap and RPS programs (see EPA-RIA, 2014).

- Extreme storm events, like Sandy, highlight the infrastructural vulnerabilities and also the institutional shortcomings in our response to such events. Some key policy recommendations to better respond to such events in the future include: investments in grid hardening and modernization, standardization of "mutual assistance" program with out-of-state utilities, and coordination of emergency response with different tiers of government and stakeholders.

- Climate change mitigation and adaptation efforts have consequences on the electricity market framework. Coupled with demand and supply-side transformations like distributed generation, demand response, and energy efficiency, the future of the power sector presents a host of opportunities and challenges for system operators and regulators.

- The current economic and regulatory policy environment calls for capacity market design changes to ensure the financial viability of fossil fuel units. The challenges associated with distributed generation, renewable intermittency, and grid reliability are likely to emerge foremost on system operator's planning agenda. There is a need to expand this scoping study to analyze the future implications for wholesale market design in a more systematic and comprehensive manner.

## 7.3 Future policy considerations

Generation of electricity contributes to nearly one-third of GHG emissions in the U.S. This contribution can be reduced substantially in the next forty years without compromising the economic growth prospects. The R/ECON-LPCEM platform, developed through this dissertation research, demonstrates the feasibility of meeting climate change challenges and emissions mitigation commitments for the Northeast

region of the U.S. In this section, I have compiled a set of policy considerations for the electric power sector based on general inferences from R/ECON-LPCEM model runs and discussions in the energy and climate change policy literature. In the future, I hope to use the R/ECON-LPCEM platform to investigate the feasibility and implications of some of these policy considerations. The following considerations could serve as a framework to implement the transformation necessary for a carbon-constrained power sector of the future.

*[1] A long-term GHG emissions reductions strategy for the electric power sector is crucial for achieving the current climate change stabilization target.*

- The LP-CEM simulation runs under various emissions cap scenarios demonstrate the feasibility of achieving "deep reductions" in $CO_2$ emissions from the power sector. Meeting the current global climate change commitment of restricting the mean temperature increase to not more than 2 degree Celsius calls for a *comprehensive, sustained and deep reduction in GHG emissions from all relevant sectors of the economy*. This calls for a simplified, long-term and market-oriented regulatory interventions to promote mitigation efforts. This should also help the economy and the industry to plan for future investments and strategies.
- EPA's proposed Clean Power Plan is a good starting step in this direction. The proposed rules will only achieve an emissions reduction of around 30% by 2030 from the *power sector* alone (EPA-RIA, 2014; Littell and Speakes-Backman, 2014; Larsen et al., 2014). This would roughly translate as a *10%* reduction in *economy-wide emissions* in 2030 compared to 2005 (assuming power sector emissions at one-third of the total). While the current policies are not likely to achieve the envisioned "deep reduction" cut in emissions of 80% or more by 2050, nevertheless they may *generate the policy momentum for further emissions reductions in the coming years*.

- The experiences of RGGI, EPA's Acid Rain program and state-level RPS programs in the U.S have shown that *market mechanisms are cost-effective in achieving the stated abatement targets*. The LP-CEM simulation runs in this research corroborates this fact for the case of $CO_2$ emissions and renewables electricity generation in the Northeast region. A sustained emissions reduction target with a gradual increase in renewables penetration level would encourage technological learning (especially for renewables and CCS technologies) and result in lower long-term societal costs.
- As noted in EPA's Regulatory Impact Analysis (EPA-RIA, 2014: p. ES-8), a *regional compliance approach is expected to result in* a *lower* compliance cost as compared to an individual state-based compliance approach. The regional compliance approach is analyzed using LP-CEM simulation runs in Chapter 5. Market-oriented mechanisms, like RGGI and California's cap-and-trade program, are expected to send efficient price signals for new investments in clean technologies and cost-effective abatement measures (Chen and Li Tseng, 2011; Hibbard et al., 2014; Larsen et al., 2014).

*[2] Policymakers should consider demand and supply-side flexibilities as part of the overall strategy to meet the challenges of climate change.*

- The electricity demand for the Northeast region alone is expected to grow at 0.2-0.45 %/year under different scenario themes (based on LP-CEM estimates). Greater efficiency in electricity usage is good for the economy and the environment. Hence a focus on *demand-side flexibilities is critical for achieving the emissions reductions commitment.*
- Demand-side management involves measures like energy efficiency, conservation and demand response programs. Although the current LP-CEM runs have not explicitly modeled these measures, they are expected to have a lower unit abatement cost when compared to renewables generation or supply-side efficiency improvements. In fact one of the key building blocks of EPA's

Clean Power Plan involves energy efficiency measure which is expected to yield 1.5% annual reduction in system demand across all states from 2020 onwards (EPA-RIA, 2014. pp. ES-1-10).

- The policymakers in the region could consider *supply-side flexibilities like combined heat and power (CHP), battery energy storage systems (BESS) and distributed generation (DG) of renewable resources as a climate change mitigation strategy*. These measures will not only reduce the transmission and distribution losses but also result in a more resilient power infrastructure. The $CO_2$ emissions reduction brought about by these flexibilities measures will also have the additional co-benefit of reducing other power sector pollutants like $SO_2$, NOx, mercury and particulate matter.

*[3] Given the modeling results and the importance of emission-free sources of power, policymakers may need to consider streamlining the institutional and regulatory processes to encourage investments in clean energy technologies (especially nuclear, renewables and carbon capture and sequestration technologies).*

- The bulk of capacity addition in the near future is expected to be natural gas based units (primarily advanced combined cycle units) for the Northeast region. This was also corroborated by the various LP-CEM simulations runs in this research. Compared to existing coal units, the combined cycle units emit half as much $CO_2$ per unit of electricity generation. *The generation of electricity from natural gas units could be sustained by appropriate carbon policies in the future*. It should be noted that natural gas capacity addition is also contingent on the coal-natural gas fuel price spread in the long-run.
- Based on the current set of LP-CEM assumptions, nuclear power generation is critical in meeting the carbon caps in the Northeast region. From an LP-CEM perspective, emissions-free power generation from baseload nuclear power plants is the most cost effective way to comply with the cap imposed by the proposed Clean Power Plan rules. Most of the existing nuclear plants in the

U.S were built in the mid-1960s to mid-1980s. These plants are scheduled to retire in the coming years. There is a lack of clarity on the future of nuclear power due to regulatory uncertainty and investment cost escalation. Federal regulators (like Department of Energy, Nuclear Regulatory Commission), industry stakeholders (like utility companies and nuclear equipment vendors), and state/regional policymakers could work collaboratively to remove the bottlenecks in: regulatory approvals for new plants and extension of operating licenses for existing plants; securing capital investments for new projects and retrofits; regulatory approvals to recover such investments from end-ratepayers; and long-term solutions to nuclear waste storage and disposal.

- Based on the results from LP-CEM simulation runs*, on-shore wind and hydro additions are considerable for the Northeast region in the next forty years*. These technologies do not require any special rebates or direct subsidies to foster their deployment (in addition to existing RECs in a RPS market). Policymakers can *augment the state-level RPS programs beyond the current mandates which expire by mid-2020s*. Promotion of renewable generation is also expected to reduce the wholesale price of electricity due to price suppression effects.
- Carbon capture and sequestration (CCS) technologies can play a crucial role in meeting the near-zero emissions level by the end of this century. In the current version of LP-CEM, technology changes has to be specified exogenously. Hence using the current cost trends of power generation, CCS is not likely to be an attractive investment option. Conventional fossil fuel units like coal and natural gas with CCS can contribute substantially to the long-term emissions reduction goal. It is estimated that an integrated combined cycle with CCS emits about 90% less $CO_2$ as compared to an existing pulverized coal unit (Morgan et al., 2005). However, the high investment costs and unit operational costs are preventing CCS technologies from being deployed on a larger scale (see Table 4.2 for a recent cost comparison of all generation technologies). Also,

there is a lack of regulatory guidelines and scientific research into the possibility of sequestering carbon in underground geological formations[64].

*[4] Given that the current modeling effort only accounts for exogenous technological improvement, a sustained effort through R&D to improve the capabilities and costs of clean energy technologies could result in reduced supply costs and increased penetration.*

- Climate change poses a lot of technological challenges for the electric power sector (like commercial adoption of CCS technologies, integrating demand and supply-side flexibilities without compromising the overall grid reliability etc.). In order to better understand and respond to these challenges, there is a *crucial need to invest more in engineering and scientific research and development (R&D) efforts*. These investments are also necessary to make clean energy technologies more cost competitive.
- In the U.S, the expenditure on power sector related R&D efforts is less than one percent of the annual electricity revenue (Morgan et al., 2005: pp.72-73; MIT, 2009. pp. 10-11). Presently, the bulk of these R&D efforts are funded through DOE-affiliated National Labs and the Electric Power Research Institute (EPRI). In light of the challenges posed by climate change, there is an urgent need to expand this research effort and encourage collaborations with private/public utilities, energy consulting firms, information technology firms and universities.

## 7.4 Research limitations and future directions

- The impact pathway of surface temperature was modeled in this research. In future, it is possible to expand the R/ECON-LPCEM platform to model the impact pathways of other physical variables like precipitation, wind speed, cloud cover and solar radiation measurement. In this research, the

[64] See EPA- Carbon Dioxide Capture and Sequestration- http://www.epa.gov/climatechange/ccs/

LDC modeling of system demand was carried out for New Jersey alone. In the future, this LDC-based demand modeling can be extended for other states and regions with appropriate Weather Response Functions (WRFs).

- For computational ease, the LP-CEM model was restricted to a linear framework. As a result, the objective functions and constraints had to be linearly formulated. Hence the emissions rate constraints (as proposed by Clean Power Plan) could not be formulated directly. Instead it was formulated as an emissions cap (a mass based cap) commensurate with the proposed $CO_2$ emissions rates for individual states. Also, the linear optimization framework does not allow for *endogenous specification of technological adaptation*. Hence the LP-CEM framework had to operate on *exogenously* specified costs of generating technologies. In the future, it may be possible to incorporate a "learning rate"-like parameter into LP-CEM without affecting the linear framework.
- In the future, it also possible to address the uncertainty in climate projections by:
    - Using projections from an ensemble of "downscaled" GCM runs (instead of relying on a single NCAR CESM run as in the current case)
    - Incorporating the parametric distribution of variables like generation outage rates and transmission loss factors in the LP-CEM framework (instead of relying on a deterministic parameters of climate change impact from the literature)
    - Running multiple simulation runs of the LP-CEM model to arrive at an expected cost estimates (i.e. using LP-CEM in a robust cost optimization approach[65]).
- For analyzing the interaction effect of carbon policies, the LP-CEM can be ramped-up for modeling the entire contiguous United States with better representation of transmission links between

[65] Shuya Li has adopted a robust cost optimization GEM/CEM model with the objective function of minimizing the expected total costs under different scenarios weighted by suitable probability measures. See Li et al. (2014).

states/sub-regions, incorporation of granular generation technology characteristics (like variable generation costs by fuel grade and dynamic heat rate estimates of generating technologies by plant age and location) and incorporation of other power sector emissions regulations (like Acid Rain Program for $SO_2$ and NOx, and mercury emissions (MATS) rules).

- The R/ECON-LPCEM modeling platform can be enhanced through a better understanding of the underlying geophysical processes behind extreme events and the associated impact pathways on the various socio-economic systems. In the near term, the model framework can be improved through a stochastic specification of damage cost function or through a robust optimization approach with suitable probability weights attached to climate-economy scenarios.
- The current version of LP-CEM operates on a marginal cost basis without accounting for risk attitudes or strategic behavior of *individual* market participants (like a generator firm or an end consumer in a market). The LP-CEM framework can be expanded to model the non-competitive behavior of market participants through an equilibrium framework or using a complementarity optimization framework linked by electricity prices (as implemented in Linares et al. (2008)). In the future, LP-CEM can be adapted to better represent the capacity, energy and ancillary services market features.

# Appendix

## Mathematical formulation of the LP-CEM model

### Set Indices

| | |
|---|---|
| ***y*** | years (alias u) |
| ***t*** | periods in each year |
| ***i*** | generation unit type |
| ***r1*** | sub-regions (alias r2) |
| ***n*** | sub-set of i containing the list of renewable generating technologies |

### Decision Variables

| | |
|---|---|
| $s_{y,r,i}$ | MW capacity installed in a given year, region and technology |
| $x_{y,t,r,i}$ | MWh generation from available units in a given year, region, time-slice and technology |
| $f_{y,t,r,1,r2}$ | MWh power transmitted from one sub-region to another in a given year and time-slice |
| ***cost*** | NPV of supply side cost |

### Parameters

| | |
|---|---|
| ***Y*** | Number of years |
| ***T*** | Number of the time periods in a year |
| ***R*** | Number of the regions |
| ***I*** | Number of generation types |
| ***N*** | Number of renewable generation types |
| ***E*** | Number of emission pollutants ($CO_2$, $SO_2$, $NO_x$) |
| $c_{y,i}$ | Generation variable cost for generation type *i* in year *y* ($/MWh) |
| $a_{y,i}$ | Investment cost for generation type *i* in year *y* ($/MW) |
| $init_{r_1,i}$ | Initial capacity of generation type i in region r1 at the beginning (MW) |
| $fnew_{y,r_1,i}$ | Forced new capacity of generation type i in region r1 with online year y (MW) |
| $fretire_{y,r_1,i}$ | Forced retirement capacity of generation type i in region r1 with retirement year y (MW) |
| $g_{y,i}$ | Fixed operation and maintenance cost for existing generation type i in year y ($/MW) |
| $h_{y,i}$ | Fixed operation and maintenance cost for new generation type i in year y ($/MW) |
| $\varphi_{y,t,r_1}$ | Demand in region r1 in time period t in year y (MWh) |
| $d_{y,t,i}$ | Climate change outage rate of generation type i in time period t in year y |
| $hours_t$ | Hours in time period *t* |
| $cf_{y,t,r_1,i}$ | Capacity factor for generation type *i* in region $r_1$ in time period *t* in year *y* |
| $peak_{y,r_1}$ | Peak load (demand) in year *y* in region *r1* (MW) |
| $m_{y,r_1}$ | Reserve margin for region *r1* in year *y* |

| | |
|---|---|
| $\boldsymbol{TMIN_{y,r_1}}$ | Yearly minimum renewable generation percentage requirement for region *r1* in year *y* |
| $\boldsymbol{EM_{e,i}}$ | Amount of pollutant *e* emitted from generation type *i* (lbs/MWh) |
| $\boldsymbol{RLEM_{e,y,r_1}}$ | Regional limit for emission gas *e* in region $r_1$ in year *y* (lbs) |
| $\boldsymbol{TL_{y,r_1,r_2}}$ | Transmission limit from region *r1* to *r2* in year *y* (MW) |
| $\boldsymbol{CL_{y,r_1,i}}$ | Yearly construction limit of generation type *i* in region *r1* in year *y* (MW) |

## Scalar

| | |
|---|---|
| r | Discount rate |

## Objective Function

$$minimize\ COST = \sum_{y=1}^{Y}\left(\frac{1}{(1+r)^y}\left(\left(\sum_{t=1}^{T}\sum_{r1=1}^{R}\sum_{i=1}^{t} x_{y,t,r1,i,}\, c_{y,i}\right)+\left(\sum_{r1=1}^{R}\sum_{i=1}^{I} s_{y,r1,i}a_{y,i}\right)+\left(\sum_{r1=1}^{R}\sum_{i=1}^{I}\left(\sum_{u=1}^{y}\left(s_{u,r1,i}+fnew_{u,r1,i}\right)\right)h_{y,i}\right)\right.\right.$$
$$\left.\left.+\left(\sum_{r1=1}^{R}\sum_{i=1}^{I}\left(init_{r1,i}-\sum_{u=1}^{y} fretire_{u,r1,i}\right)g_{y,i}\right)\right)\right)$$

## Major constraints

$$\sum_{i=1}^{I} x_{y,t,r_1,i} - \sum_{r_2=1}^{R} f_{y,t,r_1,r_2} + \sum_{r_2=1}^{R} f_{y,t,r_2,r_1} = \varphi_{y,t,r_1} \qquad \forall y,t,r_1$$

Energy constraint

$$x_{y,t,r_1,i} \le \left(init_{r_1,i} + \sum_{u=1}^{y}\left(s_{u,r_1,i} + fnew_{u,r_1,i} - fretire_{u,r_1,i}\right)\right) cf_{y,t,r_1,i} d_{y,t,i} hours_t \qquad \forall y,t,r_1,i$$

Capacity/Availability constraint

$$\sum_{i=1}^{I} init_{r_1,i} + \sum_{u=1}^{y}\sum_{i=1}^{I}\left(s_{u,r_1,i} + fnew_{u,r_1,i} - fretire_{u,r_1,i}\right) \ge peak_{y,r_1} m_{y,r_1} \qquad \forall y,r_1$$

Reserve Margin constraint

$$\sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} EM_{e,i} \le RLEM_{e,y,r_1} \qquad \forall e,y,r_1$$

Emissions limit constraint

$$\sum_{t=1}^{T}\sum_{n=1}^{N} x_{y,t,r_1,n} \ge TMIN_{y,r_1} \sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} \qquad \forall y,r_1$$

Renewable portfolio constraint

$$f_{y,t,r_1,r_2} \le TL_{y,r_1,r_2} hours_t \qquad \forall y,t,r_1,r_2$$ Transmission constraint

$$s_{y,r_1,i} \le CL_{y,r_1,i} \qquad \forall y,r_1,i$$ Construction limit constraint

$$x_{y,t,r_1,i} \ge 0,\ s_{y,r_1,i} \ge 0,\ f_{y,t,r_1,r_2} \ge 0 \qquad \forall y,t,r_1,r_2,i$$ Positive variables constraint

# LP-CEM source code (GAMS)

```
*-----------------------------------------------------------------------------------------------------------------------------------
********************************** OPTIONS ************************************
*-----------------------------------------------------------------------------------------------------------------------------------

* option is used to change defaults of GAMS for output detail, solver specific
* parameters, input program control and choice of solver
Option limrow=1000;
*This controls the number of rows that are listed for each equation in the
*EQUATION LISTING section of the listing file.
Option limcol=0;
*suppresses the COLUMN LISTING altogether for each variable (no reference map)
Option LP = Cplex ;
*cplex is an LP solver developed by IBM
Option Iterlim = 200000;
*max iteration
Option Reslim=100000000;
*max time (seconds)

file out /interface.xls/;

*-----------------------------------------------------------------------------------------------------------------------------------
********************************** SETS ****************************************
*-----------------------------------------------------------------------------------------------------------------------------------

set y years in planning horizon;
set t periods in each year;
set i generation unit type;
set egu(i) electric generation units affected by CPP;
set r1 states;
alias (r1,r2);
set existing(i) initially available generation units;
set renewables(i) possible renewable generation technologies;
set regrenewables(r1,renewables) renewables for each sub-regions;
set emission emisions considered in gep;
set dummyset1 /reserve_margin/;
set limit(i) generation units with capacity construction limits;
set transline(y,r1,r2) transmission available;
alias (y,u);
*alias: Multiple names for the same set (for cases when a set has to be
*referred to by more than one name)

$CALL GDXXRW interface_input51.xls set=y values=nodata rng=years! Rdim=1
$GDXIN interface_input51.gdx
$LOAD y
$GDXIN

$CALL GDXXRW interface_input51.xls set=t values=nodata rng=periods! Rdim=1
$GDXIN interface_input51.gdx
$LOAD t
$GDXIN

$CALL GDXXRW interface_input51.xls set=r1 values=nodata rng= states! Rdim=1
$GDXIN interface_input51.gdx
$LOAD r1
$GDXIN
```

```
$CALL GDXXRW interface_input51.xls set=i values=nodata rng=genunits! Rdim=1
$GDXIN interface_input51.gdx
$LOAD i
$GDXIN

$CALL GDXXRW interface_input51.xls set=egu values=nodata rng=eguunits! Rdim=1
$GDXIN interface_input51.gdx
$LOAD egu
$GDXIN

$CALL GDXXRW interface_input51.xls set=renewables values=nodata rng=renewables! Rdim=1
$GDXIN interface_input51.gdx
$LOAD renewables
$GDXIN

$CALL GDXXRW interface_input51.xls set=regrenewables values=nodata rng=region_renewables! Rdim=2
$GDXIN interface_input51.gdx
$LOAD regrenewables
$GDXIN

$CALL GDXXRW interface_input51.xls set=existing values=nodata rng=availableGUindex! Rdim=1
$GDXIN interface_input51.gdx
$LOAD existing
$GDXIN

$CALL GDXXRW interface_input51.xls set=emission values=nodata rng=emission! Rdim=1
$GDXIN interface_input51.gdx
$LOAD emission
$GDXIN

$CALL GDXXRW interface_input51.xls set=limit values=nodata rng=limit! Rdim=1
$GDXIN interface_input51.gdx
$LOAD limit
$GDXIN

$CALL GDXXRW interface_input51.xls set=transline values=nodata rng=transmission! Rdim=3
$GDXIN interface_input51.gdx
$LOAD transline
$GDXIN

*-----------------------------------------------------------------------------------------------------------------------
****************************** PARAMETERS ************************************
*-----------------------------------------------------------------------------------------------------------------------
* availabilityfactors (maximum possible capacity factors for all units)
$CALL GDXXRW interface_input51.xls par=capacityfactors rng=capacity_factors! Rdim=2 Cdim=1
parameter capacityfactors(t,r1,i);
$GDXIN interface_input51.gdx
$LOAD  capacityfactors
$GDXIN

* demand (system demand for each sub-region in each time-slice)
$CALL GDXXRW interface_input51.xls par=demand rng=demand! Rdim=2 Cdim=1
parameter demand(y,t,r1);
$GDXIN interface_input51.gdx
$LOAD demand
$GDXIN
```

```
* derate (climate change outage factor)
$CALL GDXXRW interface_input51.xls par=derate rng=derate! Rdim=2 Cdim=1
parameter derate(y,t,i);
$GDXIN interface_input51.gdx
$LOAD derate
$GDXIN

* dummymargin (reserve margin)
$CALL GDXXRW interface_input51.xls par=dummymargin rng=reserve_margin! Rdim=1 Cdim=1
parameter dummymargin(r1,dummyset1);
$GDXIN interface_input51.gdx
$LOAD dummymargin
$GDXIN

* emissionamount (SO2, NOx, CO2 emmision rate of generation units from each state)
$CALL GDXXRW interface_input51.xls par=emissionamount rng=EmissionAmount! Rdim=1  Cdim=2
parameter emissionamount(i,r1,emission);
$GDXIN interface_input51.gdx
$LOAD  emissionamount
$GDXIN

* CO2amount (CO2 emmision rate of generation units from each state)
$CALL GDXXRW interface_input51.xls par=CO2amount rng=CO2amount! Rdim=1  Cdim=1
parameter CO2amount(i,r1);
$GDXIN interface_input51.gdx
$LOAD  CO2amount
$GDXIN

* ratelimit (CO2 emmission limit per state per year set by CPP rules)
$CALL GDXXRW interface_input51.xls par=ratelimit rng=ratelimit! Rdim=1  Cdim=1
parameter ratelimit(y,r1);
$GDXIN interface_input51.gdx
$LOAD ratelimit
$GDXIN

* emissionlimit (SO2, NOx, CO2 emmission limit per state per year)
$CALL GDXXRW interface_input51.xls par=emissionlimit rng=EmissionLimit! Rdim=2  Cdim=1
parameter emissionlimit(y,r1,emission);
$GDXIN interface_input51.gdx
$LOAD emissionlimit
$GDXIN

* fixedcost1 (fixed cost per unit for existing unit per year $/MW)
$CALL GDXXRW interface_input51.xls par=fixedcost1 rng=fixedcost1! Rdim=1
parameter fixedcost1(i);
$GDXIN interface_input51.gdx
$LOAD fixedcost1
$GDXIN

* fixedcost2 (fixed cost per unit for forced new and new unit per year $/MW)
$CALL GDXXRW interface_input51.xls par=fixedcost2 rng=fixedcost2! Rdim=1 Cdim=1
parameter fixedcost2(y,i);
$GDXIN interface_input51.gdx
$LOAD fixedcost2
$GDXIN

* forcednew (forced new capacity)
$CALL GDXXRW interface_input51.xls par=forcednew rng=forcednew! Rdim=2 Cdim=1
```

```
parameter forcednew(y,r1,i);
$GDXIN interface_input51.gdx
$LOAD forcednew
$GDXIN

* forcedretirement (forced retirement capacity)
$CALL GDXXRW interface_input51.xls par=forcedretirement rng=forcedretirement! Rdim=2 Cdim=1
parameter forcedretirement(y,r1,i);
$GDXIN interface_input51.gdx
$LOAD forcedretirement
$GDXIN

* hours (hours in each period)
$CALL GDXXRW interface_input51.xls par=hours rng=hours! Rdim=1
parameter hours(t);
$GDXIN interface_input51.gdx
$LOAD hours
$GDXIN

* initial (initial/existing MW capacity by sub-region and technology type)
$CALL GDXXRW interface_input51.xls par=initial rng=initialcap! Rdim=1 Cdim=1
parameter initial(r1,i);
$GDXIN interface_input51.gdx
$LOAD initial
$GDXIN

* investcost (investment cost per unit for each year $/MW)
$CALL GDXXRW interface_input51.xls par=investcost rng=investcost! Rdim=1 Cdim=1
parameter investcost(y,i);
$GDXIN interface_input51.gdx
$LOAD investcost
$GDXIN

* margin
parameter margin(r1);
margin(r1)=dummymargin(r1,'reserve_margin');


* minrenewtotal (minimum renewable requirement per year)
$CALL GDXXRW interface_input51.xls par=minrenewtotal rng=minrenewtotal! Rdim=1 Cdim=1
parameter minrenewtotal(y,r1);
$GDXIN interface_input51.gdx
$LOAD minrenewtotal
$GDXIN

* peak (peak system demand for each year and sub-region)
$CALL GDXXRW interface_input51.xls par=peak rng=peak! Rdim=1 Cdim=1
parameter peak(y,r1);
$GDXIN interface_input51.gdx
$LOAD peak
$GDXIN

* totalconslimit (total technical potential for renewable resources by sub-region)
$CALL GDXXRW interface_input51.xls par=totalconslimit rng=totalconslimit! Rdim=1 Cdim=1
parameter totalconslimit(r1,renewables);
$GDXIN interface_input51.gdx
$LOAD totalconslimit
$GDXIN
```

```
* transcap (transmission capacity between sub-regions MWh)
$CALL GDXXRW interface_input51.xls par=transcap rng=trans_cap! Rdim=2 Cdim=1
parameter transcap(y,r1,r2);
$GDXIN interface_input51.gdx
$LOAD transcap
$GDXIN

* varcost (variable O&M cost per unit for each year $/MWh existing units)
$CALL GDXXRW interface_input51.xls par=varcost rng=variablecost! Rdim=1 Cdim=1
parameter varcost(y,i);
$GDXIN interface_input51.gdx
$LOAD varcost
$GDXIN

* transcost (transmission cost for each unit of MWh transmitted $/MWh)
$CALL GDXXRW interface_input51.xls par=transcost rng=trans_cost! Rdim=1
parameter transcost(y);
$GDXIN interface_input51.gdx
$LOAD transcost
$GDXIN

* transloss (transmission loss factor for each year and season)
$CALL GDXXRW interface_input51.xls par=transloss rng=trans_loss! Rdim=1 Cdim=1
parameter transloss(y,t);
$GDXIN interface_input51.gdx
$LOAD transloss
$GDXIN

* transmax (max MW transmission into a region)
$CALL GDXXRW interface_input51.xls par=transmax rng=trans_max! Rdim=1
parameter transmax(r1);
$GDXIN interface_input51.gdx
$LOAD transmax
$GDXIN

* eqvcapacity(equivalent MW capacity of a renewable generating technology)
$CALL GDXXRW interface_input51.xls par=eqvcapacity rng=eqv_capacity! Rdim=1
parameter eqvcapacity(i);
$GDXIN interface_input51.gdx
$LOAD eqvcapacity
$GDXIN

* region adjuster (investment cost adjuster depending on sub-region)
$CALL GDXXRW interface_input51.xls par=regionadj rng=regionadj! Rdim=1 Cdim=1
parameter regionadj(r1,i);
$GDXIN interface_input51.gdx
$LOAD regionadj
$GDXIN

* hrex (heat rate for exisiting units BTU/MWh)
$CALL GDXXRW interface_input51.xls par=hrex rng=hrex! Rdim=1 Cdim=1
parameter hrex(y,i);
$GDXIN interface_input51.gdx
$LOAD hrex
$GDXIN
```

```
* hrnew (heat rate for new units BTU/MWh)
$CALL GDXXRW interface_input51.xls par=hrnew rng=hrnew! Rdim=1 Cdim=1
parameter hrnew(y,i);
$GDXIN interface_input51.gdx
$LOAD hrnew
$GDXIN

* fuelcost (projected fuel cost trend for each technology $/BTU)
$CALL GDXXRW interface_input51.xls par=fuelcost rng=fuelcost! Rdim=1 Cdim=1
parameter fuelcost(y,i);
$GDXIN interface_input51.gdx
$LOAD fuelcost
$GDXIN

* tansinvs(transmission interconnection investment for each technology)
$CALL GDXXRW interface_input51.xls par=transinvs rng=transinvs! Rdim=1 Cdim=1
parameter transinvs(y,i);
$GDXIN interface_input51.gdx
$LOAD transinvs
$GDXIN
*-----------------------------------------------------------------------------------------------------------------------
********************************** MODEL ***************************************
*-----------------------------------------------------------------------------------------------------------------------

variables
exgeneration(y,t,r1,i)
newgeneration(y,t,r1,i)
flow(y,t,r1,r2)
investment(y,r1,i)
cost
;

positive variables
exgeneration(y,t,r1,i)
newgeneration(y,t,r1,i)
flow (y,t,r1,r2)
investment(y,r1,i)
;

equations
obj
energy(y,t,r1)
excapacity(y,t,r1,i)
newcapacity(y,t,r1,i)
transmission1(y,t,r1,r2)
reservemargin(y,r1)
renewabletotal(y,r1)
emission1(y,r1,emission)
climit1(i)
climit2(i)
climit3(i)
climit4(i)
climit5(i)
climit6(i)
climit7(i)
climit8(i)
climit9(i)
climit10(r1,renewables)
```

```
climit11(i)
climit12(i)
climit13(i)
climit14(i)
;

obj..
cost=e=sum(y,
     ( sum((t,r1,i),((exgeneration(y,t,r1,i)+ newgeneration(y,t,r1,i))*varcost(y,i)))
     + sum((t,r1,i),((exgeneration(y,t,r1,i)*hrex(y,i)*fuelcost(y,i))+(newgeneration(y,t,r1,i)*hrnew(y,i)*fuelcost(y,i))))
     + sum((r1,i),investment(y,r1,i)*((investcost(y,i)*regionadj(r1,i))+transinvs(y,i)))
     + sum((r1,i),forcednew(y,r1,i)*((investcost(y,i)*regionadj(r1,i))+transinvs(y,i)))
     + sum((r1,i),sum(u$(ord(u)<=ord(y)),forcednew(u,r1,i))*fixedcost2(y,i))
     + sum((r1,i),sum(u$(ord(u)<=ord(y)),investment(u,r1,i))*fixedcost2(y,i))
     + sum((t,r1),sum(r2,flow(y,t,r1,r2)*transcost(y)))
     + sum((r1,i),(initial(r1,i)-(sum(u$(ord(u)<=ord(y)),forcedretirement(u,r1,i))))*fixedcost1(i))*(1/power((1.065),ord(y)))));

energy(y,t,r1)..
(sum(r2,((flow(y,t,r2,r1)-flow(y,t,r1,r2))*transloss(y,t)))+sum(i,exgeneration(y,t,r1,i))+ sum(i,newgeneration(y,t,r1,i)))
=e=demand(y,t,r1);


excapacity(y,t,r1,i)..
exgeneration(y,t,r1,i)=l=
(initial(r1,i)-sum(u$(ord(u)<=ord(y)),forcedretirement(u,r1,i)))*derate(y,t,i)*hours(t)*capacityfactors(t,r1,i);

newcapacity(y,t,r1,i)..
newgeneration(y,t,r1,i)=l=
(sum(u$(ord(u)<=ord(y)),investment(u,r1,i))
+sum(u$(ord(u)<=ord(y)),forcednew(u,r1,i)))*derate(y,t,i)*hours(t)*capacityfactors(t,r1,i);

renewabletotal(y,r1)..
sum((t,renewables),(exgeneration(y,t,r1,renewables)+newgeneration(y,t,r1,renewables)))
=g=(minrenewtotal(y,r1)*sum((t,i),(exgeneration(y,t,r1,i)+newgeneration(y,t,r1,i)-0.0025)));

transmission1(y,t,r1,r2)$transline(y,r1,r2)..
flow(y,t,r1,r2)=l=(transcap(y,r1,r2)*hours(t));

reservemargin(y,r1)..
((sum(i,initial(r1,i))+sum((u,i)$(ord(u)<=ord(y)),forcednew(u,r1,i))-
sum((u,i)$(ord(u)<=ord(y)),forcedretirement(u,r1,i))+sum((u,i)$(ord(u)<=ord(y)),investment(u,r1,i))+ transmax(r1))- peak(y,r1))
=g=(peak(y,r1)*margin(r1));

emission1(y,r1,emission)..
sum((t,i),(exgeneration(y,t,r1,i)+newgeneration(y,t,r1,i))*emissionamount(i,r1,emission))
=l=emissionlimit(y,r1,emission);

climit1(i)..
sum((y,r1)$(ord(y)<=3),investment(y,r1,'Coal_adv'))=e=0;

climit2(i)..
sum((y,r1)$(ord(y)<=15),investment(y,r1,'NU'))=e=0;

climit3(i)..
sum((y,r1)$(ord(y)<=6),investment(y,r1,'WT_off'))=e=0;

climit4(i)..
sum((y,r1)$(ord(y)<=6),investment(y,r1,'CC_adv_seq'))=e=0;
```

```
climit5(i)..
sum((y,r1)$(ord(y)<=3),investment(y,r1,'HY'))=e=0;

climit6(i)..
sum((y,r1)$(ord(y)<=3),investment(y,r1,'CC_adv'))=e=0;

climit7(i)..
sum((y,r1)$(ord(y)<=3),investment(y,r1,'GT_adv'))=e=0;

climit8(i)..
sum((y,r1)$(ord(y)<=40),investment(y,r1,'STH'))=e=0;

climit9(i)..
sum((y,r1)$(ord(y)<=6),investment(y,r1,'Coal_adv_seq'))=e=0;

climit10(r1,renewables)..
sum(y,investment(y,r1,renewables))=l= totalconslimit(r1,renewables);

climit11(i)..
sum((y,r1)$(ord(y)<=20),investment(y,r1,'NU'))=l=3000;

climit12(i)..
sum((y,r1)$(ord(y)<=25),investment(y,r1,'NU'))=l=7000;

climit13(i)..
sum((y,r1)$(ord(y)<=30),investment(y,r1,'NU'))=l=11000;

climit14(i)..
sum((y,r1)$(ord(y)<=35),investment(y,r1,'NU'))=l=15000;


Model prob /all/ ;

Solve prob minimizing cost using LP ;

parameter exGENperU(i);
parameter exGENperRU(r1,i);
parameter exGENperYU(y,i);
parameter exGENperYRU(y,r1,i);
parameter exGEN(y,t,r1,i);
parameter newGENperU(i);
parameter newGENperRU(r1,i);
parameter newGENperYU(y,i);
parameter newGENperYRU(y,r1,i);
parameter newGEN(y,t,r1,i);
parameter totalinv(i);
parameter yearlyinvest(y,i);
parameter totalinvregion(r1);
parameter invs(r1,y,i);
parameter trans(y,t,r1,r2);
parameter transin(y,t,r2);
parameter transout(y,t,r1);
parameter totalcost;
parameter dualenergy(y,t,r1);
parameter dualcapacity(y,r1);
parameter dualrenewabletotal(y,r1);
parameter dualemission(y,r1,emission);
```

```
dualenergy(y,t,r1)=energy.m(y,t,r1);
dualcapacity(y,r1)=reservemargin.m(y,r1);
dualemission(y,r1,emission)=emission1.m(y,r1,emission);
dualrenewabletotal (y,r1)= renewabletotal.m (y,r1);
totalcost=cost.l;

loop((y,i),yearlyinvest(y,i)=sum(r1,investment.l(y,r1,i))+sum(r1,forcednew(y,r1,i)));
loop(r1,totalinvregion(r1)=sum((y,i),investment.l(y,r1,i))+sum((y,i),forcednew(y,r1,i)));
loop(i,totalinv(i)=sum((y,r1),investment.l(y,r1,i))+sum((y,r1),forcednew(y,r1,i)));
loop((y,r1,i),invs(r1,y,i)=investment.l(y,r1,i)+forcednew(y,r1,i));
loop((y,t,r1,i),exGEN(y,t,r1,i)=exgeneration.l(y,t,r1,i));
loop((y,t,r1,i),newGEN(y,t,r1,i)=newgeneration.l(y,t,r1,i));
loop((i),exGENperU(i)=sum((y,t,r1),exgeneration.l(y,t,r1,i)));
loop((i),newGENperU(i)=sum((y,t,r1),newgeneration.l(y,t,r1,i)));
loop((r1,i),exGENperRU(r1,i)=sum((y,t),exgeneration.l(y,t,r1,i)));
loop((r1,i),newGENperRU(r1,i)=sum((y,t),newgeneration.l(y,t,r1,i)));
loop((y,i),exGENperYU(y,i)=sum((t,r1),exgeneration.l(y,t,r1,i)));
loop((y,i),newGENperYU(y,i)=sum((t,r1),newgeneration.l(y,t,r1,i)));
loop((y,r1,i),exGENperYRU(y,r1,i)=sum((t),exgeneration.l(y,t,r1,i)));
loop((y,r1,i),newGENperYRU(y,r1,i)=sum((t),newgeneration.l(y,t,r1,i)));


*-----------------------------------------------------------------------------
********************************** OUTPUT ************************************
*-----------------------------------------------------------------------------

execute_unload "GEM_output.gdx" dualenergy
execute 'gdxxrw.exe GEM_output.gdx  par=dualenergy rng=energy($perMWh)! '

execute_unload "GEM_output.gdx" dualcapacity
execute 'gdxxrw.exe GEM_output.gdx  par=dualcapacity rng=capacity! '

execute_unload "GEM_output.gdx" dualemission
execute 'gdxxrw.exe GEM_output.gdx  par=dualemission rng=emission! '

execute_unload "GEM_output.gdx" dualrenewabletotal
execute 'gdxxrw.exe GEM_output.gdx  par=dualrenewabletotal rng=renewabletotal! '

execute_unload "GEM_output.gdx" totalcost
execute 'gdxxrw.exe GEM_output.gdx  par=totalcost rng=totalcost! '

execute_unload "GEM_output.gdx" exGEN
execute 'gdxxrw.exe GEM_output.gdx  par=exGEN rng=exGen(MWh)! '

execute_unload "GEM_output.gdx" newGEN
execute 'gdxxrw.exe GEM_output.gdx  par=newGEN rng=newGen(MWh)! '

execute_unload "GEM_output.gdx" exGENperU
execute 'gdxxrw.exe GEM_output.gdx  par=exGENperU rng=exGenperU(MWh)! '

execute_unload "GEM_output.gdx" newGENperU
execute 'gdxxrw.exe GEM_output.gdx  par=newGENperU rng=newGenperU(MWh)! '

execute_unload "GEM_output.gdx" exGENperRU
execute 'gdxxrw.exe GEM_output.gdx  par=exGENperRU rng=exGenperRU(MWh)! '
```

```
execute_unload "GEM_output.gdx" newGENperRU
execute 'gdxxrw.exe GEM_output.gdx  par=newGENperRU rng=newGenperRU(MWh)! '

execute_unload "GEM_output.gdx" exGENperYU
execute 'gdxxrw.exe GEM_output.gdx  par=exGENperYU rng=exGenperYU(MWh)! '

execute_unload "GEM_output.gdx" newGENperYU
execute 'gdxxrw.exe GEM_output.gdx  par=newGENperYU rng=newGenperYU(MWh)! '

execute_unload "GEM_output.gdx" exGENperYRU
execute 'gdxxrw.exe GEM_output.gdx  par=exGENperYRU rng=exGenperYRU(MWh)! '

execute_unload "GEM_output.gdx" newGENperYRU
execute 'gdxxrw.exe GEM_output.gdx  par=newGENperYRU rng=newGenperYRU(MWh)! '

execute_unload "GEM_output.gdx" yearlyinvest
execute 'gdxxrw.exe GEM_output.gdx  par=yearlyinvest rng=yearlyinvest(MW)! '

execute_unload "GEM_output.gdx"  totalinvregion
execute 'gdxxrw.exe GEM_output.gdx  par=totalinvregion rng=totalinvregion(MW)! '

execute_unload "GEM_output.gdx"  totalinv
execute 'gdxxrw.exe GEM_output.gdx  par=totalinv rng=totalinv(MW)! '

execute_unload "GEM_output.gdx"  invs
execute 'gdxxrw.exe GEM_output.gdx  par=invs rng=invs(MW)! '
```

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