ROBUST OPTIMIZATION OF ELECTRIC POWER GENERATION EXPANSION PLANNING CONSIDERING UNCERTAINTY OF CLIMATE CHANGE

By

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ABSTRACT OF THE THESIS

Robust Optimization of Electric Power Generation Expansion Planning

Considering Uncertainty of Climate Change

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Thesis Director:

Dr. David W. Coit

This research is dedicated to the study of electric power system generation expansion planning considering uncertainty of climate change. Policymakers across the world are increasingly concerned about the effects of climate change and its impact on human systems when making decisions. Electric power Generation Expansion Planning (GEP) problems that determine the optimal expansion capacity and technology under particular technical constraints, given cost and policy assumptions are undoubtedly among those decisions. Now and in the future, climate change is and will be affecting new power plant investment decisions and the electricity generation system in more uncertain ways. The power system needs to be more reliable, cost-effective and environmentally friendly when exposed to higher temperature, less precipitation and more intense and frequent extreme events. However, incorporating the climate change effects into a GEP model has rarely been attempted before in the literature. The best approach to comprehensively model those uncertainties into electricity generation, and to optimize the generation planning under uncertainty needs be studied in a more specific way.

In this research, a preliminary GEP model is proposed with available input data from various resources. Discrete scenarios and robust optimization are adopted to specifically model uncertainty. Relationships between climate change and GEP parameters are defined and considered in each scenario. The preliminary GEP model is then solved under each scenario to identify the climate change impact on the generation expansion planning decision. Two robust optimization models are presented and solved to find the optimal results under uncertainty: Model 1 is expected total cost minimization and Model 2 is maximum regret minimization. Both models find a compromise solution that is good for all scenarios, which avoids the possible risk associated with a poor decision that is only optimal for one particular scenario. The results suggest recommendations for further power system uncertainty modeling and risk management.

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This section provides an introduction of the background knowledge involved in this research, and a general outline of the work. The electric power system, the generation expansion planning problem, the relationship between climate change and power system are briefly introduced. The problem statement and objective of this study are presented thereafter.

1.1 Power System

An electric power system is a network of electrical components used to supply, transmit and use electric power. In the United States, electric energy sales have grown to well over 400 times after the 1970s. The installed kW capacity per capita in the U.S. is estimated to be close to 3 kW [22].

An interconnected power system is a complex enterprise that may be subdivided into the four major subsystems:

- Generation;
- Transmission and Sub-transmission;
- Distribution;
- Load.

The generators produce power whose voltage is then increased, and an overhead transmission network transfers power from generating units to the distribution system. Then the distribution system distributes lower voltage power to retail consumers. Figure 1 is a simplified illustration of the power system.

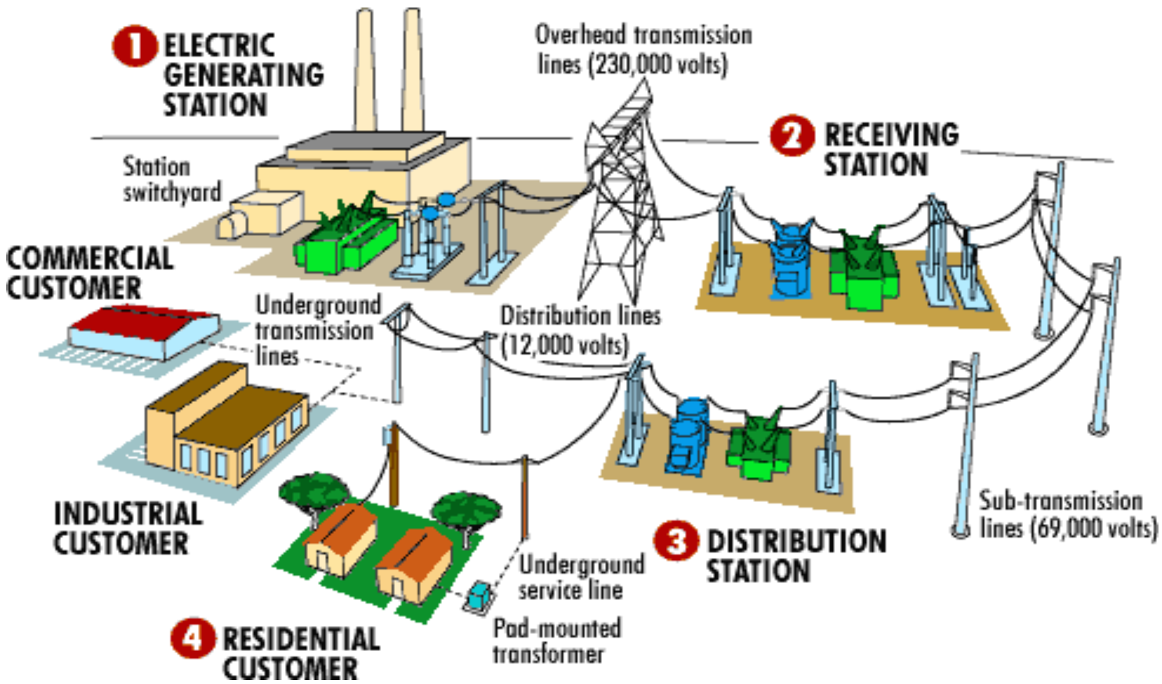

Figure 1 Power system [70]

There are three large power grids in the continental U.S., Eastern Interconnection, Western Electricity Coordinating Council, and Electric Reliability Council of Texas. The electric power industry in the U.S. has changed since the deregulation of the telecommunication, gas, and other industries. The generation business is rapidly becoming market-driven. The industry now faces new challenges and problems associated with the interaction of power system entities in their efforts to make crucial technical decisions while striving to achieve the highest level of human welfare [22].

1.2 Generation Expansion Planning (GEP)

Electricity consumption is considered as an important component of a country's economy. Expansion planning of electric power systems involves many elements such as generation, transmission, distribution, load, equipment, construction, and operation in the system. Researchers have to consider all the technologies and resources used in different subsystems to meet the changing demand over a short or long time horizon.

The electricity generation expansion planning (GEP) problems focus on the generation part of the power system. The objectives are to determine the optimal selection of generation technologies at the right time and right place to construct them. The problem is solved to ensure an economic, reliable, and environmentally acceptable supply according to the predicted demand, over a given planning horizon based on particular technical constraints, cost and policy assumptions.

1.3 Climate Change and Power System

Climate change is a significant and lasting change in weather patterns. It can be caused by factors such as biotic processes, variations in solar radiation received by Earth, plate tectonics, and volcanic eruptions and certain human activities [75]. In recent decades, human activities are identified as the significant driving force of “global warming” [76].

Particular indicators can reflect climate change, such as ocean surface temperature, sea level, ice sheet, precipitation and so on. At least three major climate variables are relevant to the power system [36]:

- Temperature;
- Precipitation;
- Extreme events.

Figures 2-5 show the historical data of some climate variables in the past 30 years of the United States. Figure 2 is the average annual temperature; Figure 3 shows the number of days exceeding 100℉ in summer 2011. Figure 4 is the average annual precipitation, and Figure 5 is a summary of climate disasters.

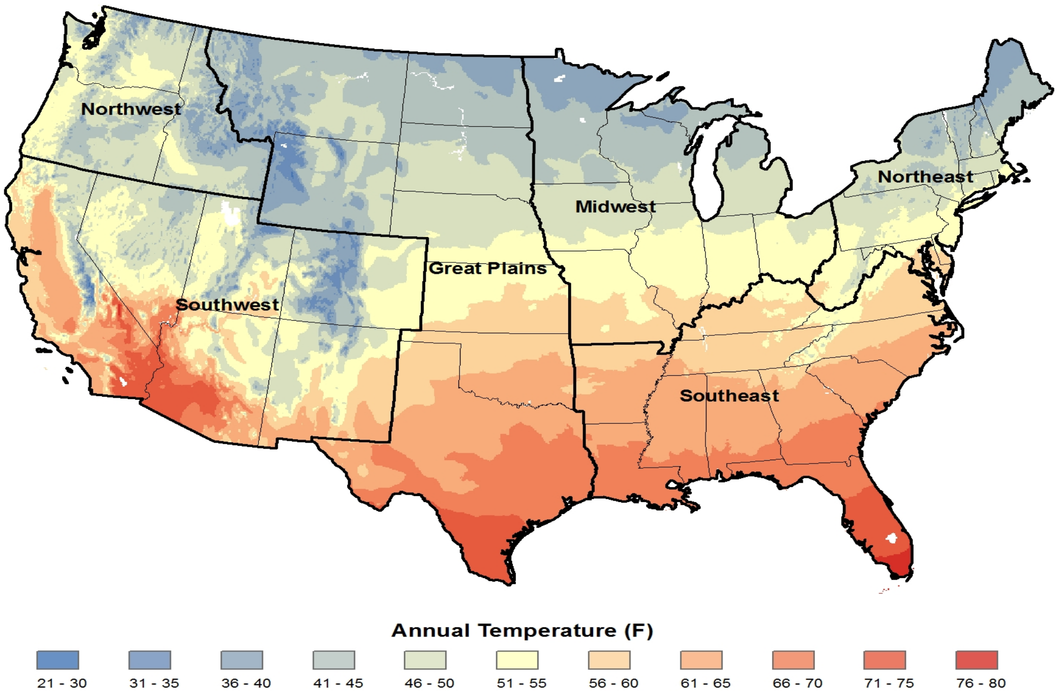

Figure 2 Average annual temperature (°F) of the U.S. (1981-2010) [32]

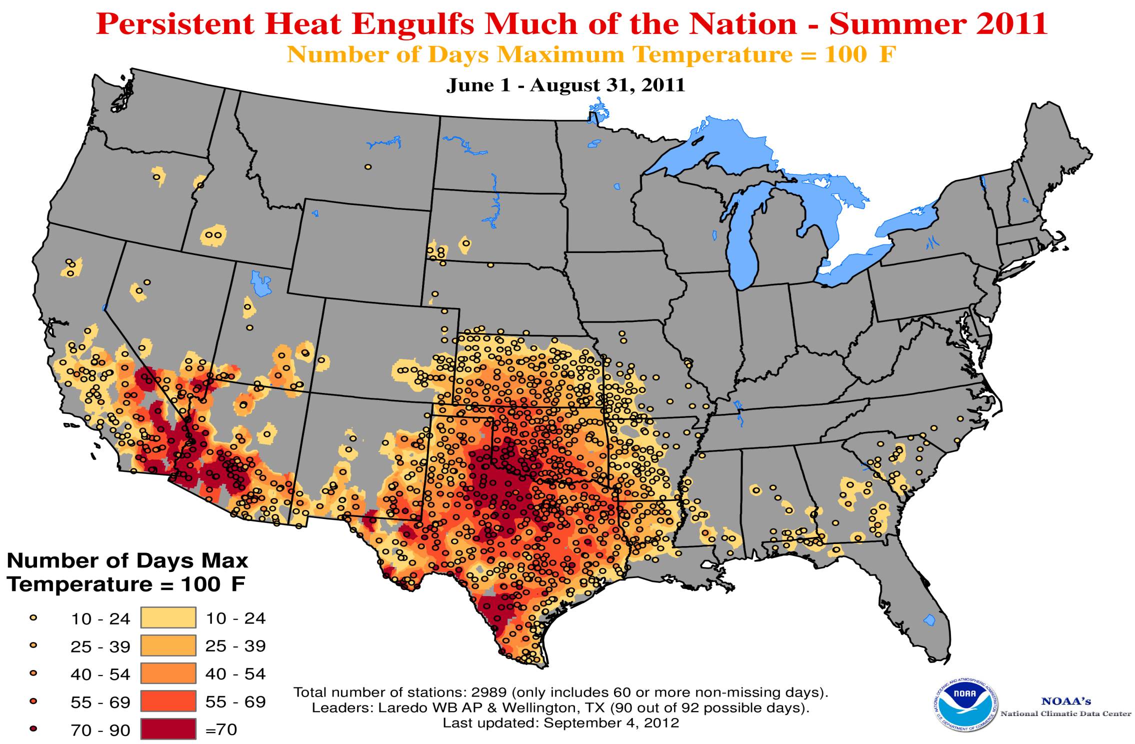

Figure 3 Number of days with maximum temperature exceeding 100°F in Summer 2011 across the U.S. [32]

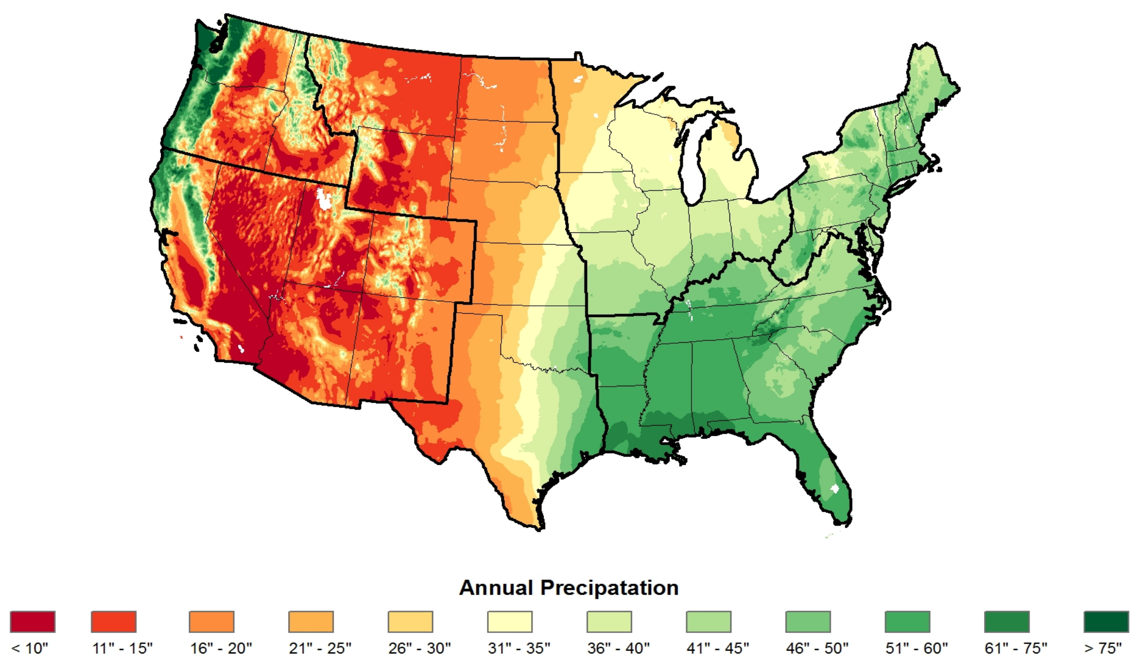

Figure 4 Average annual precipitation (inches) of the U.S. (1981-2010) [32]

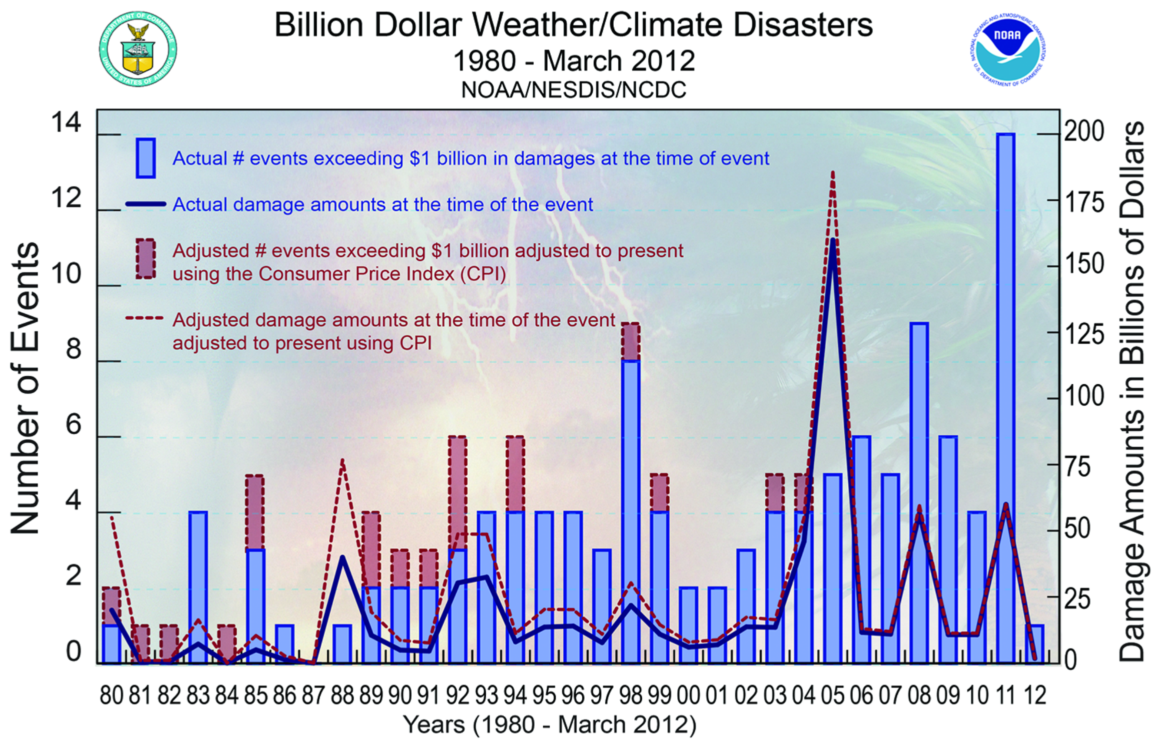

Figure 5 Annual number of weather events causing at least $1 billion in losses in the U.S. [32]

All these climate variables have more or less impacts on the generation, transmission, distribution and demand for electricity (Figure 6). In the long term, it must be assured that sufficient and flexible generation capacity is planned and constructed to meet anticipated growing demand and unpredictable climate disasters, recognizing that the costs of associated with short-term variability are absorbed and passed on to consumers.

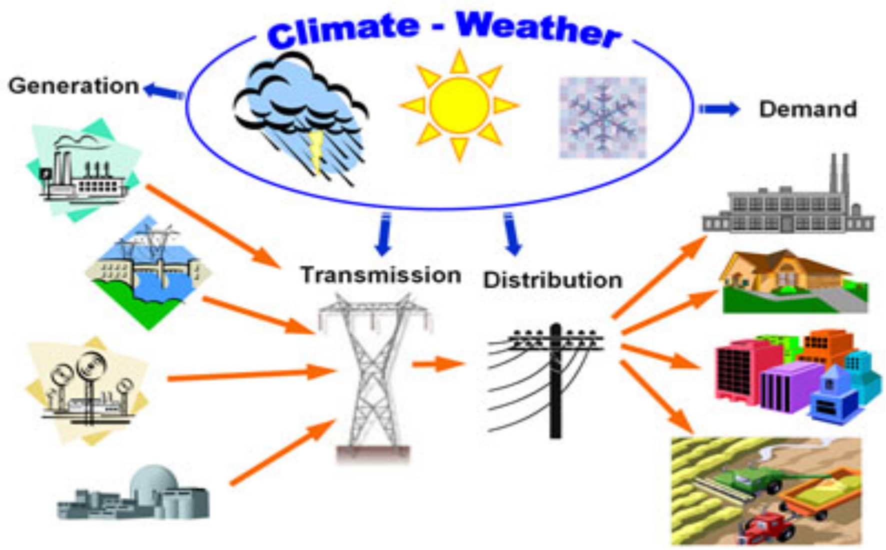

Figure 6 Climate change and power system [71]

While climate change remains uncertain in local and short-term variations, appropriate adaptation and mitigation in response to global climate trends is urgent and necessary. The power system is facing four impacts brought on by the climate change.

- Higher temperatures will increase summer cooling demands and peak loads, and decrease heating demands in winter. Net energy demand is projected to increase as rising cooling demands outpace declining heating demands.
- Seasonal and long-term change pattern of precipitation, streamflow, runoff and snowpack will impact cooling water availability for electricity generation.
- Extreme events are affecting electricity generation, transmission and distribution facilities. The frequency and intensity of extreme events are expected to increase.
- In the longer term, sea level rise will affect coastal facilities and infrastructure.

Some of the effects of climate change are projected to occur in all regions whereas others may vary more by region. However, regional variation does not imply regional isolation as energy systems have become increasingly interconnected.

Compounding factors may create additional challenges [36], which brings more challenges in the study of power system and climate change.

1.4 Problem Statement

Now and in the future, climate change is and will be affecting new power plant investment decisions and electricity generation plans in more uncertain ways. It is desired that the power system should be more reliable, cost-effective and environmentally friendly when confronted with higher temperature, more extreme events and unpredictable climate change. Traditional GEP modeling is not sufficient because uncertain GEP problems with climate change consideration are necessary to be solved.

To rigorously consider the uncertainty of climate change, this study adopts discrete scenarios method and robust optimization. It aims at finding an optimal expansion plan including investment, generation and transmission, which is effective for possible climate scenarios assuming discrete probability distributions. In another words, the objective is to select a compromise solution under discrete climate scenarios, avoiding the possible risk brought on by a poor decision that is only optimal for one particular scenario. Possible risks can be either investing too much capacity and having too much electricity or not meeting demands and requirements under some scenarios, which can be then quantitatively defined as the "regret." In either case, "regret" is interpreted as the difference between the desired cost in one particular scenario and the realistic cost under uncertainty.

This study starts with a preliminary GEP model with all the variables and parameters well defined and available data from various sources, which includes existing capacities, projected future electricity demands and peak demands, emission and transmission limits, etc. Then, the uncertainty of climate change is taken into consideration, as the parameters that are directly or indirectly impacted by the climate change have been quantifiably specified. The methodology of scenarios is used instead of the unknown continuous probability density functions to make the problem tractable. The preliminary GEP model is then solved under each scenario to identify the climate change impact on the generation expansion planning decision. After that, two robust optimization models are presented and solved to determine the optimal results under uncertainty: Model 1 is expected total cost minimization and Model 2 is maximum regret minimization. In both models, global robust constraints are used for all scenarios by incorporating penalty costs of each scenario. Sensitivity analyses and comparisons between results are conducted and conclusions are made thereafter.

The scope of this research study is limited to New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut), New York State and the PJM Interconnection (all or most of Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia and West Virginia, parts of Indiana, Illinois, Kentucky, Michigan, North Carolina and Tennessee). The geographic areas of Independent System Operator of New England (ISO-NE), New York Independent System Operator (NYISO) and PJM Interconnection are shown in Figures 7-9.

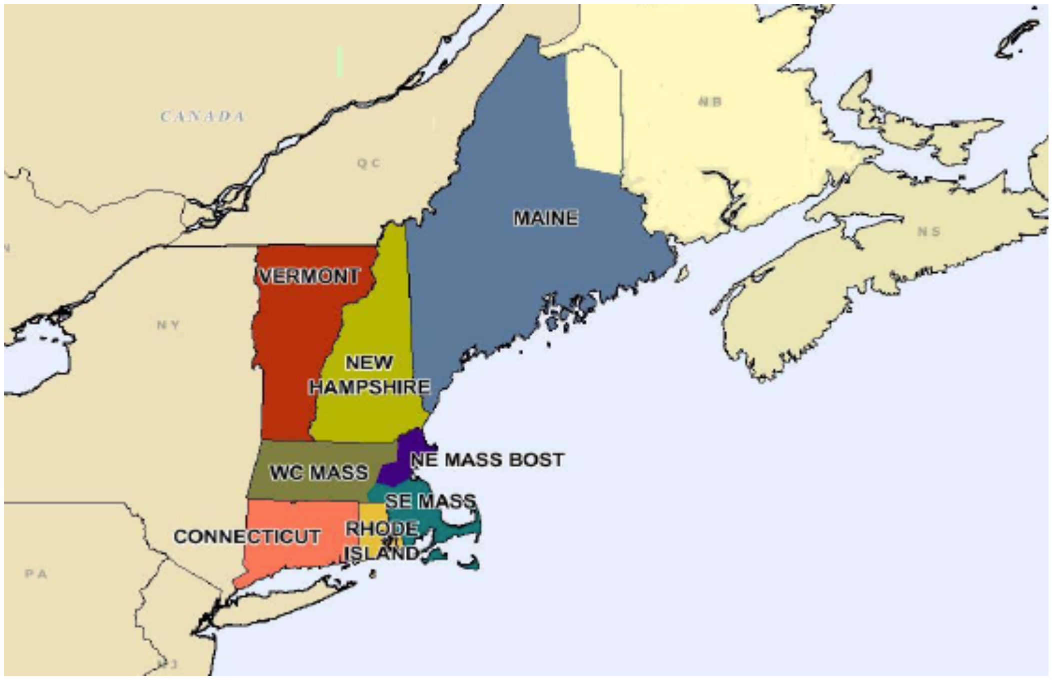

Figure 7 Independent System Operator of New England (ISO-NE) map [72]

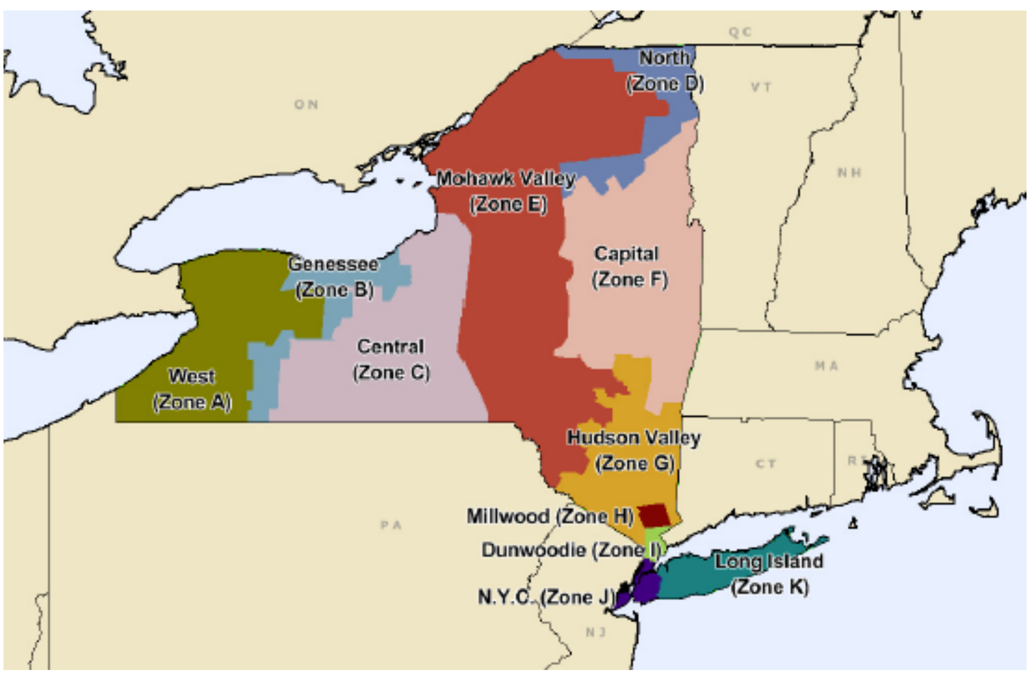

Figure 8 New York Independent System Operator (NYISO) map [72]

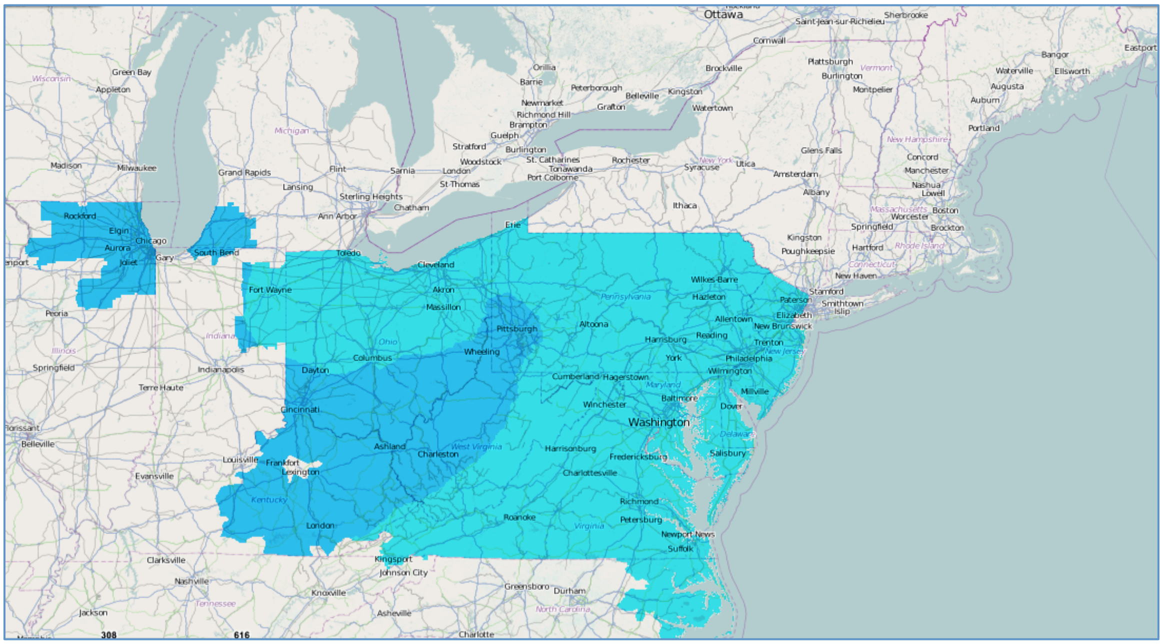

Figure 9 PJM Interconnection map [73]

1.5 Objectives

The major objectives of this research are:

- Specify the basic GEP model with input data of the Northeastern region and validate the basic model with numerical tests;
- Identify variables in the basic model that are affected by climate change and define quantifiable relationships between climate change and GEP parameters;
- Define discrete climate scenarios that approximate the possible futures and each scenario is an independent sample path with corresponding realization of relevant climate variables: temperature, precipitation and extreme events;
- Solve the preliminary model under each scenario, compare the optimal solutions in each case and identify the climate change impact on the expansion decisions;

- Establish two mathematical robust optimization models: Model 1 minimizing the expected total cost, Model 2 minimizing the maximum "regret";
- Solve the robust optimization models, perform sensitivity analysis and comparisons.

2 Background and Literature Review

This section provides an overview of GEP problem formulation and definition, various generation technologies and summary of the literature on climate change and different types of GEP problems. Based on the objective of this research, the literature review is presented in three subsections:

- Climate change;
- Climate change's impact on power system;
- GEP problems: Least-cost GEP problems, GEP problems considering uncertainty and GEP problems with environmental consideration.

2.1 GEP Problem Definition and Formulation

The GEP problem is to determine the optimal planning decision that involves the technologies and resources to satisfy the increasing power demand. Least-cost and multi-objective GEP problems, as well as different solution techniques have been well studied in the past forty years.

A typical GEP optimization model has 1) a planning horizon, 2) an economic objective minimizing the present value of the total cost or maximizing social economic welfare, 3) a set of constraints including capacity limitations, environment regulations, price, customer demands and so on, 4) a set of the decision variables representing the operating and expansion options.

Because of the complexity of involved factors and computation in GEP problems, a multitude of GEP problems based on different assumptions, predictions, objectives, uncertainties, mathematical solution techniques are also studied.

Buehring et al. [23] presented the major issues in the GEP problems: 1) uncertain demand, 2) technology options, including existing and potential future options, 3) economic evaluation, which takes inflation and real discount rate into consideration, 4) reliability, considering many factors such as forced outage, variation in demand, scheduled maintenance and so on, 5) constraints, such as transmission, reserve margin, availability of resources, infrastructure needs, environmental considerations and policies.

2.2 Generation Technologies

Various technologies are employed in electricity generation systems. Typical sources are coal, petroleum, natural gas, nuclear and renewable sources like solar, wind, hydro, geothermal and biomass. For example, according to the study of U.S. Energy Information Administration (EIA), the percentage of U. S. electricity generation resources by capacity (MW) are shown in Figure 10 and U.S. electricity generation amounts from 1990-2040 are shown in Figure 11, with fuel generation percentages. While electricity demand is growing, emission-related problems are more significant and harmful. As a result, clean energy is gradually replacing fossil energy in the diverse field. As projected in Figure 11, nearly 20% of total electricity generation is shifting from coal and other fossil fuels to renewables and natural gas from 2000 to 2040.

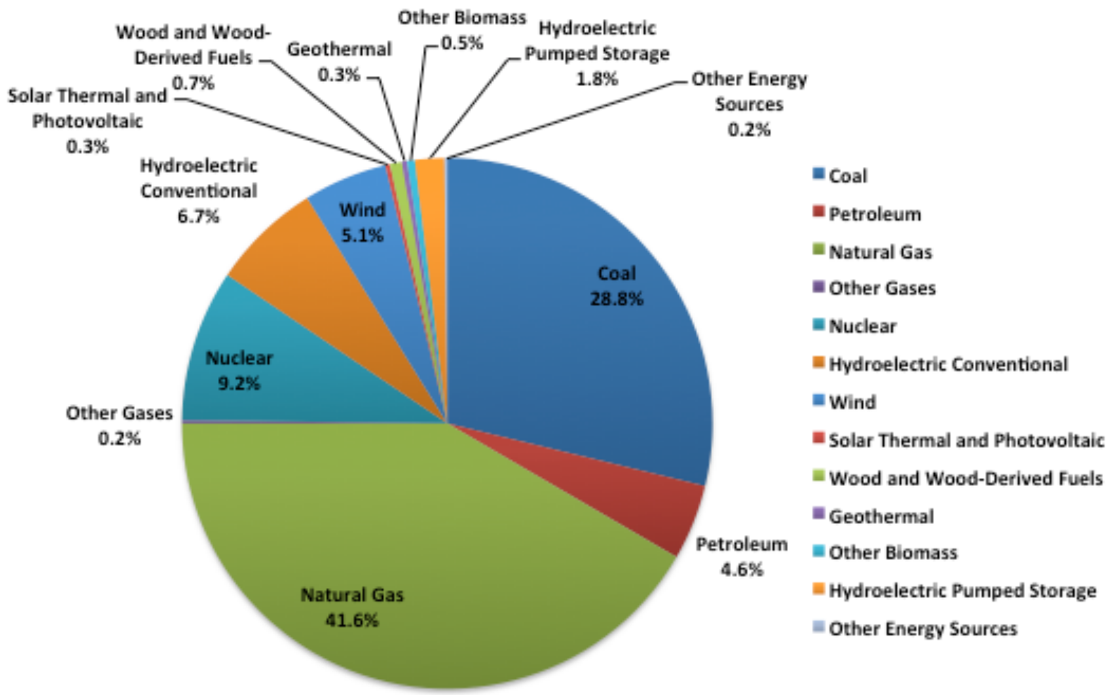

Figure 10 2012 U.S. electricity generation sources [62]

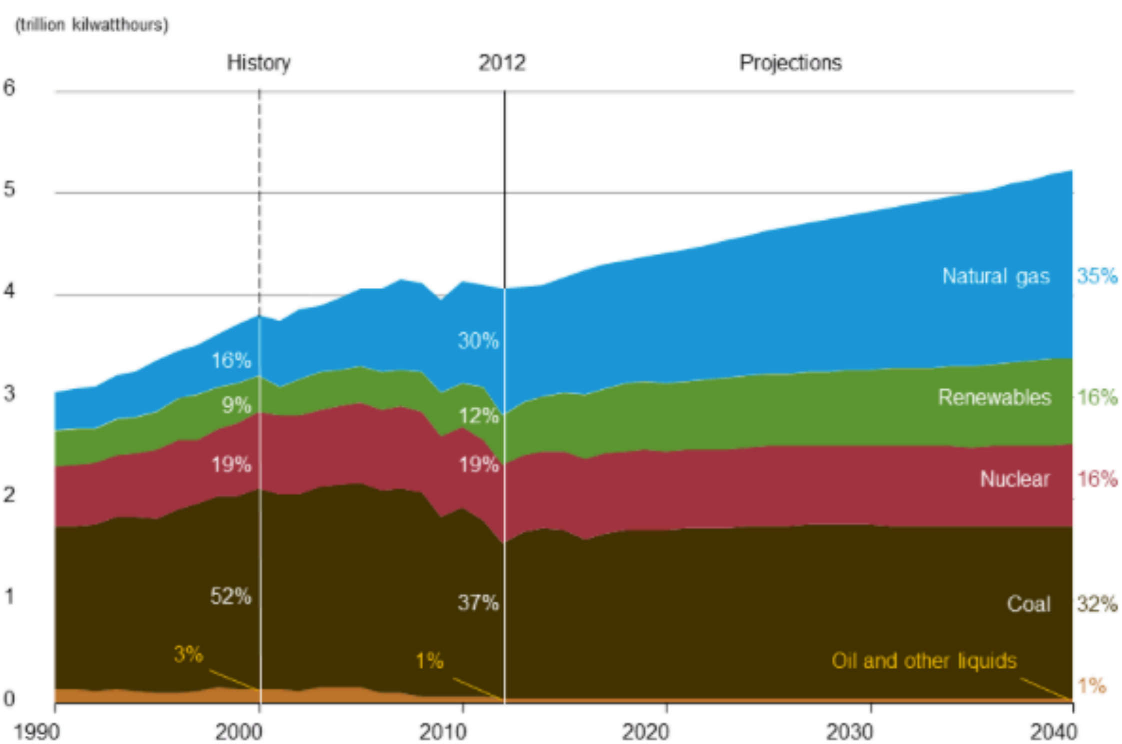

Figure 11 U.S. electricity generation by fuel 1990-2040 (trillion kilowatt-hours) [69]

Electricity load demand can be divided into "base load", "intermediate load", and "peak load." Based on the generation technology operational characteristics and the relative fixed including capital and variable costs, different types of fuels or combination of fuels are needed to fulfill one or more of these three types of demand. Figure 12 is a typical yearly load curve with different generation technologies for each type of demand.

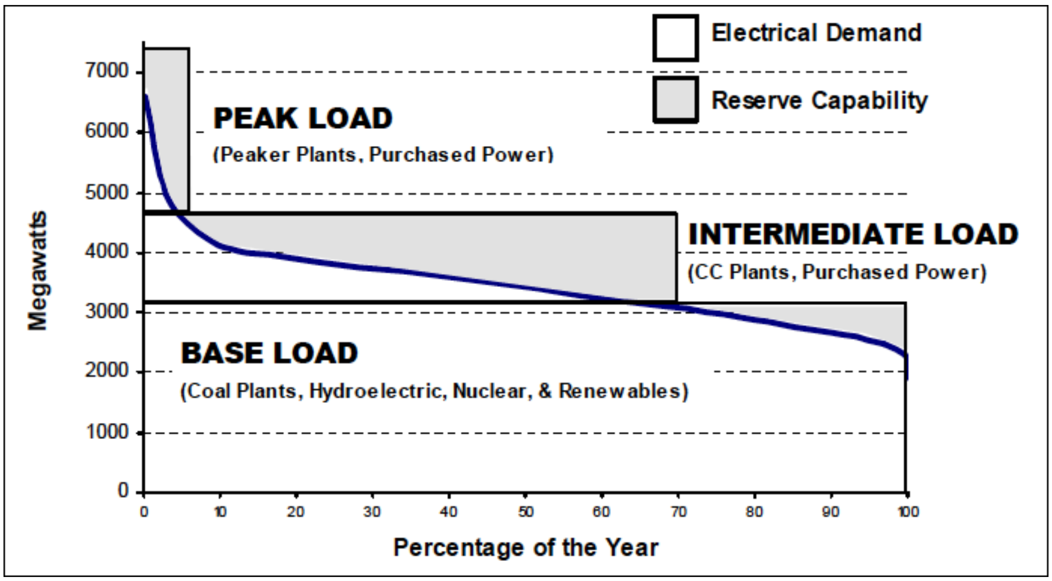

Figure 12 Electricity load curve and types of different load demand in a year [74]

2.3 Climate Change

The Special Report on Emissions Scenarios (SRES) [33] prepared by Intergovernmental Panel on Climate Change (IPCC) in 2000 presents several scenarios including socio-economic ones, the resulting carbon dioxide levels and the consequent changes in global temperatures and sea levels. It considers different storylines of population projection, economic and social development, energy and technology, agriculture and land-use emissions, other greenhouse as emissions, and policies, etc. The set of scenarios consists of six scenario groups summarized from the four storylines and families: one group each in A2, B1, B2, and three groups within the A1 family, characterizing alternative developments of energy technologies: A1FI (fossil fuel intensive), A1B (balanced), and A1T (predominantly non-fossil fuel). This is widely used in the literature for projection of climate change.

The Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX) [39] presented by IPCC in 2012 assesses numerous papers and reports on issues that range from observations of exposure, vulnerability, climate extremes, impacts and disaster losses to the implications for future disaster risk management, social and sustainable adaptation and development. It aims to provide background and resources for decision-makers to prepare effectively for managing the risk of extreme events.

The U.S. National Oceanic and Atmospheric Administration (NOAA) Technical Report of Regional Climate Trends and Scenarios for the U.S. National Climate Assessment (NCA) is a complete and targeted synthesis of historical and emission-dependent future climate conditions associated with two pathways of greenhouse gas emissions based on IPCC emission scenarios. There are nine reports in this series, one for the contiguous U.S. [32] and one each for eight regions defined by the NCA, Northeast [40], Southeast, Midwest, Great Plains, Northwest, Southwest, Alaska and Hawaii/Pacific Islands.

In the U.S. Global Change Research Program (USGCRP) report [51] and National Climate Assessment Development Advisory Committee (NCADAC) draft climate assessment report [49], comprehensive impacts of climate change on Americans' health and livelihoods and the ecosystems are assessed and summarized. For instance, water resources, energy supply and use, agriculture, transportation, human health, etc. These references are very useful in understanding climate change impacts and preparing for these challenges.

2.4 Climate Change's Impact on Power System

It is the greenhouse gas emission, mainly carbon dioxide, associated with humanity's production and use of energy is a primary cause of global warming, and in turn, climate change will eventually affect our production and use of energy [51]. The interaction of climatic, environmental and human factors makes the effects of climate change complex and uncertain. Researchers start to study the impacts on power systems in the most recent decade.

Pilli-Sihvola et al. [17] examine the impact of a gradually warming climate on the need for heating and cooling with an econometric multivariate regression model for five countries in Europe along the south–north line. The predicted changes in electricity demand are then used to analyze how climate change impacts the cost of electricity use, including carbon costs.

Franco and Sanstad [18] use historical data on electricity consumption and construct some simple regression estimation of the electricity demand based on the IPCC's emissions scenarios. Ahmed et al. [19] use multiple linear regression analysis for the historical climatic and non-climatic variables to establish a correlation between per capita electricity demand and associated key variables. Time series analysis is then performed to predict future temperature and corresponding cooling and heating degree days of New South Wales, Australia.

The Sixth Northwest Conservation and Electric Power Plan [34] models climate change as a random variable and shows that the uncertainty in the climate change analyses is much larger than the uncertainty surrounding the current climate. In order to incorporate climate change uncertainty into the model as a random variable, the relative likelihood of occurrence for each climate scenario must be known. Then for each future examined, one particular climate change profile would be selected as one of the many random variables used for that particular future.

U.S. Department of Energy [36] presents a report regarding the climate change vulnerabilities in the energy sector and the adaptation responses and future opportunities. They summarize various literatures and projections of climate change's impact on the energy sectors, and identify future challenges and opportunities. Several major climate trends are considered: increasing air and water temperatures, decreasing water availability in some regions and seasons, increasing intensity and frequency of storms events, flooding, and sea level rise. Exploration and production, transportation, generation, renewable energy, electric grid and energy demand are the major energy sectors discussed in the report.

Urban and Mitchell [37] focus on the impacts of disasters brought by climate change, assess the vulnerability of various electricity generation options such as fossil fuels, nuclear power, hydropower and renewable energy to changing disaster risks and address the implications for electricity generation planning and policy.

U.S. Climate Change Science Program [38] summarizes what is currently known about the effects of climate change on energy production and use in the United States. Any of these climate change effects could have very significant impacts for energy policies, decisions, and institutions in the U.S., affecting discussions of courses of action and appropriate strategies for risk management. It answers three questions for improving adaption and mitigation:

- "How might climate change affect energy consumption in the U.S.?
- How might climate change affect energy production and supply in the U.S.?
- How might climate change have other effects that indirectly shape energy production and consumption in the U.S.?"

Miller et al. [41] emphasize the extreme heat events in California, which is defined as temperature threshold for the 90th-percentile exceedance probability (T90) of the local warmest summer days under the current climate. They project the T90 events and predict that the electricity demand is going to increase under both higher and lower emission scenarios and is likely to challenge current-day providers.

Mirasgedis et al. [42] develop two statistical forecasting models on a daily and monthly basis respectively for electricity demand in Greece. The effect of the climatic conditions on the electricity demand is then further investigated via predictions under four different scenarios for the weather conditions of the coming year, which include both normal and recently observed extreme behavior.

Crowley and Joutz [43] investigate the climate change-driven effects on electricity demand. They construct scenarios to present the impact of a 2 degree Fahrenheit increase in temperature and simulate the short-run and long-run energy consumption. The output from the short-run and long-run consumption models in terms of load projections and elasticities then serve as the inputs to supply side models that allocate or dispatch the electricity from the generation stock and mix to meet the load.

2.5 Generation Expansion Planning Models

2.5.1 Least-cost Generation Expansion Planning Models

Most GEP problems are least-cost single objective problems, minimizing the investment and operating cost over a planning period, but multi-criteria modeling with economic and environmental factors has been analyzed in detail in the past recent years. These factors may be included in the single objective, or one of the multiple objectives.

Bloom [8] solves a least-cost GEP problem using a mathematical programming decomposition technique. The paper takes system reliability into consideration, by adding an expected unserved energy constraint. The planning problem is decomposed into a master problem and a set of sub-problems. The master problem is a LP problem that generates a trial solution and the sub-problem minimizes the total cost of this solution. The sub-problem has the form of a non-linear integral equation, but can be solved using probabilistic simulation. Then the solution can be found in an iterative way.

Based on the generalized Benders' decomposition of Bloom's work [8]-[9], Sirikum et al. [5] provide a genetic algorithm heuristic-based method called GA-Benders' decomposition to solve the GEP problem. They consider the constraints of the power demands, power capacities, loss of load probability levels, locations and emission limitations. It is a large-scale mixed integer nonlinear programming problem, but can be efficiently solved by the GA-BD method.

Kagiannas et al. [3] review the GEP methods used in a competitive electric power generation market. Game theoretic modeling is usually used in GEP problems considering dynamics of electricity markets. Chuang et al. [4] present an application of non-cooperative game theory for GEP in a competitive electricity industry. They apply the Cournot model of oligopoly competing behavior, incorporated operational considerations such as plant capacity limitations and energy balance constraints. Results show that Cournot competition leads to greater industry expansion and system reliability, while a monopoly expansion may lack sufficient incentive to introduce new technologies.

Meta-heuristic techniques are also widely used in GEP modeling. Kannan et al. [10] present an application and comparison of meta-heuristic techniques including genetic algorithm, differential evolution, evolutionary programming, evolutionary strategy, ant colony optimization, particle swarm optimization, tabu search, simulated annealing and hybrid approach.

Kannan et al. [24] also present the application of particle swarm optimization and its five variants to the least-cost GEP problem. The virtual mapping procedure and penalty function approach are addressed to reduce the number of infeasible solutions that appear in the subsequent iterations. Results show that the particle swarm optimization performs better than dynamic programming when the planning horizon is longer.

Fukuyama and Chiang [25] use a parallel genetic algorithm to solve long-range GEP problem. A test system with four technologies, five intervals and various numbers of generation units prove the high efficiency of coarse-grain parallel genetic algorithm with decimal coding.

Park et al. [6] propose an evolutionary programming algorithm to solve the least-cost GEP problem. A novel domain mapping procedure is presented, which maps yearly cumulative capacity vectors into one dummy vector, and quadratic approximation tournament selection are used to enhance the efficiency.

Park et al. [7] also apply an Improved Genetic Algorithm (IGA), which incorporates an artificial initial population scheme, a stochastic crossover technique, elitism and scaled fitness function, to solve long-term least-cost GEP problems. Two traditional shortages in mathematical programming are overcome, and the IGA can find a better solution in a reasonable computation time.

2.5.2 Generation Expansion Planning Models Considering Uncertainty

A lot of studies employ deterministic modeling, but in recent years researchers have realized that it is necessary to include the uncertainty in future conditions. There are enormous uncertainties in the field of GEP. Hobbs [1] provides us a review of uncertainties that utilities must consider in resource planning in Table 1.

Table 1 Uncertainties in GEP problems [1]

I.	*Market/demand uncertainties*
•	Load growth
•	Price elasticities
•	Market for off-system sales & purchases
•	Competition with non-electric fuels
II.	*Resource uncertainties*
•	Technological developments
•	Availability, initial costs of resource options
•	Construction times
•	Fuel prices, emission allowance prices
•	Generating unit availability
•	Climate change, water supplies

•	Amount, dependability of nonutility generation
•	Customer response to Demand-Side Management (DSM) programs
•	Dependability and persistence of DSM
III.	*Legal and economic uncertainties*
•	Inflation, interest rate, economic growth
•	Government policies concerning ratemaking, cost recovery
•	Environmental regulations
•	Municipalization/government takeover
•	Public concerns

Cazalet [27] may be one of the earliest research efforts that consider uncertainty in the GEP problem. A decomposition method is firstly applied to stochastic power plant planning. Then based on this work, Borison et al. [26] introduce a primal-dual method that solves the dynamic probabilistic problem using simple static deterministic solution techniques. The main problem is decomposed into a set of linked static deterministic problems, where the linkages are forced through Lagrange multipliers. These problems are solved separately in a primal iteration, while the multipliers are updated in a dual iteration. The name "State-of-the-world" (time and outcome) in their research is defined as a scenario.

Gorenstin et al. [14] describe a methodology for GEP under uncertainty. The paper summarizes three classes of techniques to solve the least-cost GEP problem: decomposition and stochastic optimization, decision analysis, and multi-objective tradeoff analysis. As described in the paper, the deterministic equivalent approach is not used; instead, several scenarios with probabilities are given, and the stochastic optimization aims to find an optimal solution that gives satisfactory results for all scenarios, which is a “robust model.” Two formulations are given in the paper, which are minimization of expected costs and minimax regret function.

Malcolm et al. [15] develop a similar robust optimization model for GEP under uncertain power demand. They introduce a set of independent scenarios with assigned probabilities. Then they consider two types of error: surplus capacity and unmet demand. In the objective function, except for the expected total cost, they also include a weighted variance of scenarios and a weighted penalty of errors. The test problem shows the optimal solution is “almost” optimal for any realization of the demand scenarios.

Buehring et al. [23] introduce STATS (Stochastic Analysis of Technical Systems) model based on Monte Carlo simulations with uncertain costs of technologies. They apply probabilistic value distributions for cost components and performance factors, and relationships between component costs are modeled through correlations. Although the exact cost is still unknown, the relationship or comparison between several technologies using similar components can be simulated, and then the investment of one technology can be decided.

Mo et al. [16] consider the uncertainty in energy demand, prices of energy carriers (electricity) and dynamics of the system with a dynamic programming approach. They use discrete time Markov chains to depict the variables such that these variables have a year-to-year independence. The problem is transformed to a problem minimizing expected cost with Markov chains. However, due to the assumptions of independence, whether Markov chains is adequate to simulate the raw data needs further study.

Su et al. [12] propose a dynamic programming (DP) GEP problem incorporated with a fuzzy technique. The only objective is minimizing the cost, but a fuzzy constraint is used for environment protection. With the fuzzy technique, the original DP paths and states can be reduced for the ease of computation.

Ahmed et al. [28] address a GEP problem with uncertainties in demand and cost parameters, and economies of scale in expansion costs. The uncertain parameters are assumed to evolve as a discrete time stochastic process with a finite probability space. Using a scenario tree approach to model the evolution of uncertain parameters, they develop a multi-stage integer stochastic programming formulation. By reformulating the original model in different ways (stochastic lot-sizing, Krarup-Bilde, heuristic method, branch-and-bound), they obtain tighter LP relaxation gaps, and thus solve the problem to global optimality.

Schaeffer and Szklo [29] consider the uncertainty in the policies that will affect electricity demand and supply and subsequent environmental burdens in Brazil. They add a cogeneration module that can assess the portion of the electric power market to the model and compare three scenarios including the business-as-usual case. The total cost in the emissions of environmental scenario seems to be much better than the environmentally desirable technologies scenario and the base case.

2.5.3 Generation Expansion Planning Models with Environmental Considerations

When considering the environment, most researchers focus on the impact as a part of the objective function, or one of multiple objectives. Kim and Ahn [13] present a multi-criteria model considering cost, CO_2 emissions, nuclear hazards and solve it by applying Mitten's preference-order dynamic programming to WASP (Wien Automatic System Planning Package).

Diakoulaki and Karangelis [30] examine four mutually exclusive scenarios for the expansion of the Greek electricity system. In the first methodology, they consider the economic, technical and environmental performance as the criteria, and give each of them a weight that sums up to 1. The cost-benefit analysis is presented as an alternative method, and they assign each of the indices a generalized cost, so the objective is to minimize the total cost.

Meza et al. [31] describe a multi-period multi-objective GEP model solved by a linear programming method (max-min, min-max, compromise programming, and weighted approach) and the analytical hierarchy process. Minimizing the total cost including investment, operational and transmission costs, as well as minimizing the emission, the imported fuel and the energy price risks are the objectives of the model.

Tekiner et al. [2] propose a mixed integer linear program model integrated with reliability, dispatching decision, reducing air emission, centralized and distributed power generation over a multi-period planning horizon. They include the unmet demand cost and revenue from steam into the total cost, and by using Monte-Carlo simulation, numerous scenarios considering the availability of the system components are randomly determined. Then the Pareto front for different weights on the objectives are found, and the trade-offs between the cost and environmental impacts are presented.

2.5.4 Conclusion of Generation Expansion Planning Literature Review

To summarize, environmental factors are mostly considered in the model output, but modeling climate change variables and impacts is rarely studied in the GEP literature.

Some researchers that have noticed the uncertain climate change are using simple statistical models, and only focusing on the demand part of the GEP problem. In fact, many other elements in the generation expansion are impacted by the climate change, such as transmission capacity, generation capacity, maintenance, and so on, which should be specifically and systematically studied.

Many GEP models that consider uncertainty and various solution methods have been studied and implemented. These ideas can be adopted to address climate change. Dynamic programming, decomposition, discrete time stochastic process, fuzzy theory, scenarios are widely utilized in this field.

Single objective least-cost and multi-objective models are well developed during the past few decades, and they established the foundation of further GEP models. Numerous algorithms have been applied efficiently, and meta-heuristic methods are becoming popular as the scale of the problems become larger.

Future study for GEP modeling lies in:

- Development of multi-criteria models with different policies, environmental consideration, sustainable resources, reliability and so forth;
- Better and more efficient method or program to solve the larger-scale problem;
- Inclusion of uncertainties brought by the economic, environmental and technological changes;
- Better coordination with different subsystems of the power system.

2.6 Methodologies

In this research, we adopt the methodologies of discrete scenarios and robust optimization to solve optimization models with uncertain parameters. Expected total cost minimization is well developed, while maximum regret minimization is rather new. Therefore, we present an introduction section for both scenario and minmax regret modeling.

2.6.1 Scenario Definition

Scenario analysis is a common tool in the field of stochastic programming, aiming at approximating future uncertainty through a finite set of scenarios with a discrete probability distribution. Each scenario corresponds to a realization of a random variable over the planning horizon and has an associated realization probability with it [64]. Scenarios should be designed to capture the realistic range of all relevant sources of uncertainty at a computational acceptable number. Meanwhile, extreme scenarios with low probability are necessary to be included for the consideration of model robustness.

There exist two common ways of describing the set of all possible scenarios. In the interval data case, each numerical parameter can take any value between a lower and an upper bound. In the discrete scenario case, the scenario set is described explicitly [68]. In our research, the emphasis is on discrete scenarios. Scenarios are used in [2, 14, 25, 26, 28, 29, 30] to interpret various uncertainties (costs, demands, policies) considered in the GEP models. Climate scenarios are used in [34, 42, 43] to specifically represent uncertainty in weather conditions in the future.

2.6.2 Minmax Regret Models

"Regret" is also called "opportunity loss" in some literature, and maximum regret is then the worst-case opportunity loss. Averbakh [67] defines the regret as the absolute (or relative) deviation of the objective function value from the best possible one under this scenario. One can refer to [66, 67, 68] for detailed mathematical formulations of different approximations of minmax regret modeling.

Gorenstin et al. [14] describe a linear programming minimax regret function used in GEP model with uncertainty in 1970. They define the regret as the difference between the actual cost and the cost that would have been incurred if there was prior knowledge that a given scenario would take place. Due to a great variability in the investment and operation costs for various scenarios, the minimax regret model can be an alternative way to obtain a "robust solution."

Bean and Hoppock [65] study the least-risk metric that also assures low relative costs by "minimizing the maximum regret" of generation plans. They study the Shoreham nuclear power plant in New York as motivation. It took twenty years to construct, was nearly 100 times over budget, and was mothballed before entering commercial operation. Therefore, it is attractive to identify a low cost and low risk plan across all possible scenarios. They describe the procedure of minimization of maximum regret modeling as follows:

Step 1: Calculate the net present value of total system cost for each investment option or investment portfolio across all scenarios.

Step 2: Create a matrix of total costs for each investment option in every scenario. Determine the least-cost investment option in each scenario.

Step 3: Calculate a regret score for each investment option across all scenarios by subtracting the least-cost option from each investment option within each scenario. Create a matrix of regret scores.

Step 4: Determine the maximum regret of each investment option by selecting the maximum regret score for each investment option across all scenarios. Determine the investment option with the lowest maximum regret. This option minimizes the maximum forecast regret.

For example, Bean and Hoppock [65] give an example of four scenarios and three investment decisions, with optimal decisions highlighted in red in Figure 13, which lists the performance of investment decisions under each scenario. Investment A seems to be an optimal solution as it is optimal for three out of four scenarios. However, from the perspective of maximum regret as shown in Figure 14, investment B performs better. In fact, a finite set of possible solutions are numerated in their study, the matrix of solution scenario combination can be easily evaluated.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Investment A	*$ 100 B*	*$120 B*	*$125 B*	*$140 B*
Investment B	*$103 B*	*$123 B*	*$127 B*	*$131 B*
Investment C	*$110 B*	*$125 B*	*$128 B*	*$130 B*

Figure 13 A typical GEP scenario analysis output, depicting net present value total system costs for each investment scenario combination [65]

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Maximum Regret of Each Investment
Investment A	$ 0 B	$0 B	$0 B	$10 B	$10 B
Investment B	$3 B	$3 B	$2 B	$1 B	$3 B
Investment C	$10 B	$5 B	$3 B	$0 B	$10 B

Figure 14 A regrets table quantifying the potential risk for each investment [65]

Jiang et al. [66] also give an example of decision making under uncertainty as shown in Figure 15. For different objective considerations such as expected cost, maximum cost and maximum regret, the optimal solution may be rather distinct.

		Decision		
Scenario	Probability	A	B	C
S1	0.10	$100	$50	$60
S2	0.90	$20	$50	$30
Expected Cost		$28	$50	$33
Maximum Cost		$100	$50	$60
Maximum Regret		$50	$30	$10

Figure 15 Decision making under uncertainty [66]

The two examples illustrated above both have a finite set of feasible solutions; decision makers only need to choose one of them. In reality, we are not so sure about the feasible solutions, and thus, the method of Gorenstin et al. [14] can be used to solve stochastic programming on an infinite set of alternative solutions.

3 Preliminary Model

In this section, the preliminary model with its inputs is presented. Data is collected from various sources, and all the assumptions are made according to the availability of the data. The mathematical model and its nomenclature are then defined.

3.1 Model Inputs and Assumptions

The preliminary model is a fundamental linear programming GEP problem. The scope of this research study is limited to New England (Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut), New York State and the PJM Interconnection (All or most of Delaware, District of Columbia, Maryland, New Jersey, Ohio, Pennsylvania, Virginia and West Virginia, parts of Indiana, Illinois, Kentucky, Michigan, North Carolina and Tennessee), the time horizon is between 2010 and 2040. The input data is gathered from various sources such as Eastern Interconnection Planning Collaborative (EIPC) [59], National Renewable Energy Laboratory (NREL) [60], U.S. Environmental Protection Agency (EPA) [61], U.S. Energy Information Administration (EIA) [62].

3.1.1 Geographic Regions

The regions considered in this study are: NEISO, NYISO_A-F, NYISO_G-I, NYISO_J-K, PJM_E, PJM_ROM, PJM_ROR, which are shown in Figure 16 as indicated by the dashed rectangle. The names of these regions come from three Regional Transmission Organizations (RTO) in the Eastern Interconnection grid of North America: NEISO- Independent System Operator of New England, NYISO-New York Independent System Operator, PJM-PJM Interconnection. New York state is divided into eleven sub-regions A-K, we consider Upstate (A-F), Lower Hudson Valley (G-I), New York City/Long Island (J-K) as three big sub-regions. We consider PJM Eastern Mid-Atlantic Area Council (NJ, DE, east MD), PJM Rest of Mid-Atlantic Area Council (east PA, DC, west MD), PJM Rest of Regional Transmission Operator (north IL, OH, west PA, west MD, WV, VA, east NC) as three big sub-regions.

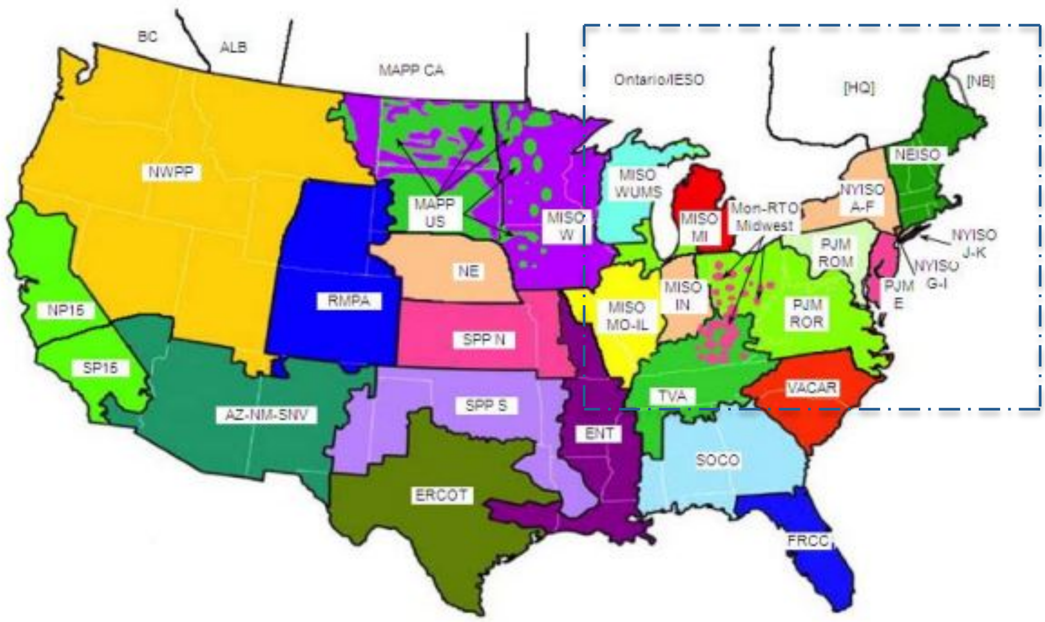

Figure 16 Map of considered areas in the model [59]

3.1.2 Demands and Peak Demands

We divide a year into three seasons: summer, winter, and spring/fall. The summer is defined as May through September, the winter includes December, January, February. Spring/fall is named shoulder in the study, which includes March, April, October, and November. The time periods are defined as summer-peak, summer-offpeak, shoulder-peak, shoulder-offpeak, winter-peak, winter-offpeak. Tables 2-3 give the electricity demands and peak demands in 2010 and projected growth rates 2010-2040.

Table 2 Electricity demands and peak demands in 2010 (GWh) [59]

	NEISO	NYISO_A-F	NYISO_G-I	NYISO_J-K	PJM_E	PJM_ROM	PJM_ROR
Summer-peak	30,115	14,710	5,048	19,759	38,078	35,124	124,635
Summer-offpeak	23,953	12,918	4,001	15,185	29,507	28,614	102,943
Shoulder-peak	20,773	10,908	3,266	12,162	23,305	23,731	84,720
Shoulder-offpeak	18,014	9,985	2,858	10,495	20,819	21,511	78,294
Winter-peak	16,628	8,687	2,601	9,229	18,642	19,527	68,549
Winter-offpeak	14,608	8,021	2,329	8,196	16,948	17,856	63,614
Peak (MW)	26,043	11,455	4,356	17,030	32,910	27,332	99,146

Table 3 Electricity load growth rate [59]

	NEISO	NYISO_A-F	NYISO_G-I	NYISO_J-K	PJM_E	PJM_ROM	PJM_ROR
Annual load growth							
2010-2020	0.23%	0.2%	0.14%	0.39%	-0.98%	0.86%	0.4%
2021-2040	0%	0.51%	0.85%	0.88%	0.67%	0.67%	0.61%
Peak load growth							
2010-2020	0.49%	0.1%	-0.09%	0.1%	-0.92%	0.71%	0.42%
2021-2040	0.12%	0.51%	0.85%	0.88%	0.67%	0.67%	0.61%

3.1.3 Generation Technologies

The existing, new and renewable generation technology types are shown in Table 4. Table 5 gives a summation of characteristics of generation technologies. Existing capacity at the beginning of the planning horizon is listed in Table 6. We also consider the capacity factor for each type of generation technology, forced new builds with online year, forced retirements with retire year [59]. We do not include the investment costs of forced new plants in our expansion costs, because it is sunk costs. To be precise on the definition of capacity factor, it is the potential availability of each generation unit, as an upper bound of generation output. For example, the onshore class 3 wind turbine has a capacity factor of 0.1781 during summer peak in NEISO, which means at most 17.81% of time the wind turbine can work due to insufficient wind power or other conditions.

Table 4 Generation technologies [59]

	Generation Type	Description
Existing	CC	Combined Cycle - Natural Gas
	Coal	Steam Turbine - Coal
	CT	Combustion Turbine - Natural Gas or Oil
	GEO (Renewable)	Geothermal
	HY (Renewable)	Hydro - Conventional
	LFG (Renewable)	Landfill Gas
	NU	Nuclear
	PS (Renewable)	Hydro - Pumped Storage
	PV (Renewable)	Solar - Photovoltaic
	ST (Renewable)	Solar - Solar Thermal/Solar Power
	STOG	Steam Turbine - Oil/Gas
	STWD	Steam Turbine - Wood
	WT (Renewable)	Wind Turbine onshore
New	WT_on3 (Renewable)	Wind Turbine (onshore class 3 wind)
	WT_on4 (Renewable)	Wind Turbine (onshore class 4+ wind)
	WT_off (Renewable)	Wind Turbine offshore
	IGCC	Integrated Gasification Combined Cycle
	IGCC_seq	IGCC with carbon capture/sequestration
	AC	Advanced or Pulverized Coal

Biomass (Renewable)	Biomass

Note: WT_on3 and WT_on4 are both onshore wind turbine technologies but have different target wind resources (depending on the wind power, wind can be divided into different classes, we consider class 3 and class 4+ wind), they are only distinguished for new generation units

Table 5 Characteristics of all generation technologies [59, 60]

Type	Outage rate	Inv. cost (2010$/kW)	Fixed OM (2010$/kW) Existing	Fixed OM (2010$/kW) New	Var. cost [62] (2010$/MWh)	SO_2 (lbs/MWh) [61]	NO_X (lbs/MWh) [61]	CO_2 (lbs/MWh) [61]
CC	6.1%	1,035	29.68	14.39	47.45	0.1	1.7	1,135
Coal	6.5%	-	48.22	-	28.63	13	6	2,249
CT	9%	711	-	6.7	78.43	0.66	2.9	1,565
GEO	13%	4,163	89.76	84.27	0	0	0	0
HY	4.9%	-	14.24	-	0	0	0	0
LFG	5%	2,525	120.65	120.33	0	0.8	5.4	2,988
NU	3.2%	5,615	112.77	88.75	12.06	0	0	0
PS	4%	-	23.74	-	5.98	0	0	0
PV	60%	4,777	14.66	16.7	0	0	0	0
ST	1%	4,714	60.32	64	0	0	0	0
STOG	6.7%	-	37.15	-	58.82	3	2.4	1,325
STWD	10%	-	32.05	-	78.43	3	4	1562
WT	0%	-	34.22	28.07	0	0	0	0
WT_on3	0%	2,460	34.22	28.07	0	0	0	0
WT_on4	0%	2,460	34.22	28.07	0	0	0	0
WT_off	0%	5,997	-	53.33	0	0	0	0
IGCC	8%	3,262	-	48.9	44.12	0.13	0.4	1,540
IGCC_seq	8%	5,389	-	69.3	53.04	0.13	0.4	154
AC	6%	2,885	-	29.67	30.1	0.13	1.6	1,540
Biomass	7.5%	3,901	-	100.5	41.47	28.6	11	0

Note: investment costs are not listed for some technologies that are not allowed to invest

Table 6 Existing generation capacity in 2010 (MW) [59]

	NEISO	NYISO_A-F	NYISO_G-I	NYISO_J-K	PJM_E	PJM_ROM	PJM_ROR
CC	11,463	3,594	1,157	3,658	7,649	3,986	10,542
Coal	2,570	2,252	369		3,853	16,381	59,868
CT	2,384	260	152	4,948	6,899	3,555	21,073
HY	1,933	4,395	32		258	1,236	1,604
LFG	532	166	64	124	462	338	482
NU	4,645	3,197	2,045		8,472	5,036	20,000
PS	1,674	1,412			400	1,513	3,081
PV	2				22	4	24
STOG	6,236	1,701	2,431	6,799	3,252	4,109	2,122
STWD	609	86				70	194
WT	202	1,283			10	731	2,597

3.1.4 Emission Limits

Considered emissions from different types of generation technologies are SO_2, NO_X, and CO_2 in this study. Emission limit assumptions are made according to the 2011 real emission data of included states [62]. Since the geographical boundaries of the considered region do not exactly match with boundaries of the states, reasonable assumptions are needed. As shown in Table 7, 110% of the real emissions in 2011 from New Jersey and Delaware are used as the 2010 emission limit of PJM_E, 110% of the real emissions in 2011 from Pennsylvania, Maryland, District of Columbia serve as the 2010 emission limit of PJM_ROM, and the 2010 PJM_ROR emission limit is 1.1 times of total emissions from Ohio, Virginia, West Virginia in 2011. New York State real emissions in 2011 are equally divided into three parts, and 1.1 times of each part is the

2010 emission limit for NYISO_A-F, NYISO_G-I and NYISO_J-K. Due to the environmental consideration, we assume a mandatory declining rate of 0.5% every year.

Table 7 Emission limits in 2010 (lbs)

	SO_2	NO_X	CO_2
NEISO	140,150,241	88,884,873	91,435,710,713
NYISO_A-F	41,959,533	34,467,164	30,121,374,938
NYISO_G-I	41,959,533	34,467,164	30,121,374,938
NYISO_J-K	41,959,533	34,467,164	30,121,374,938
PJM_E	32,428,935	42,031,490	50,559,872,517
PJM_ROM	879,357,749	420,002,006	342,555,176,849
PJM_ROR	1,746,512,807	436,214,048	371,550,964,554

3.1.5 Transmission Limits

Transmission within regions is also allowed and it is associated with a transmission capacity (see Table 8). It is assumed that transmission capacity remains constant throughout the planning horizon. Transmission lines are limited to the sub-region, Canadian and other states' transmission are neglected, and transmission losses are not included.

Table 8 Transmission capacity in 2010 (MW) [59]

	NEISO	NYISO_A-F	NYISO_G-I	NYISO_J-K	PJM_E	PJM_ROM	PJM_ROR
NEISO		600	600	430			
NYISO_A-F	600		4,250			1,000	
NYISO_G-I	600	1,999		6,130	1,500		
NYISO_J-K			1,999				

PJM_E			500	330		8,000	
PJM_ROM		2,000			8,000		8,000
PJM_ROR						8,000	

3.1.6 Construction limits

New investments are limited by construction limits as shown in Tables 9-10. Table 9 regulates a five-year construction limits for some technologies, while no limits for others, and Table 10 specifies the available new resource limit for each technology in each region. The construction time is omitted in this research, which means the new generation unit will be available immediately after the investment.

Table 9 Yearly construction limits (MW) [59]

	2015	2020	2025	2030	2035	2040	2045	2050
AC	0	2,500						
NU	0	0	3,750	12,500	25,000	37,500	50,000	62,500
WT_on	0	426						
WT_off	0	10,454						
Biomass	0	4,192	8,383	12,575	16,766			
PV	0	2,769						
LFG	0	864	1,755	2,619				
IGCC_seq	0	500	3,000	8,000				
IGCC	0	1,500						

Table 10 Regional construction limits (MW) [59]

	NEISO	NYISO_A-F	NYISO_G-I	NYISO_J-K	PJM_E	PJM_ROM	PJM_ROR

CC							
Coal	0	0	0	0	0	0	0
CT							
GEO	0	0	0	0	0	0	0
HY	0	0	0	0	0	0	0
LFG	710	446	223	446	142	284	368
NU			0	0			
PS	0	0	0	0	0	0	0
PV	12,000	4,000	2,000	4,000	2,000	4,000	6,916
ST	0	0	0	0	0	0	0
STOG	0	0	0	0	0	0	0
STWD	0	0	0	0	0	0	0
WT	0	0	0	0	0	0	0
WT_on3	16,900	12,700	300	200	3,200	5,800	50,400
WT_on4	5,280	840	60	170	470	1,230	3,200
WT_off	8,500	500	200	2,400	9,600	16,900	20,200
IGCC							
IGCC_seq	4,000			0			
AC	0	0	0	0	0		
Biomass	1,700	1,000	818	0	332	2,357	10,556

Note: 0 here means no available resources or no construction is allowed, while blank cell means unlimited construction.

3.1.7 Other Assumptions

Electric power systems should always have excess capacity to maintain reliability. Reserve margin is (capacity minus demand)/demand, where "capacity" is the expected maximum available supply and "demand" is expected peak demand [62]. For instance, a reserve margin of 0.15 means available generation capacity is 15% more than the expected peak demand. Reserve margin requirements for each region can be found in [59].

RPS (Renewable Portfolio Standard), which is a regulation that requires the increased production of energy from renewable energy sources, specifies the percentage of renewable energy generation in each region [59].

Some factors are omitted due to their complexity and data unavailability. For example, emissions trade market is growing because of some environmental regulations, but this may relate to many other policies and regulations. Therefore, trade is avoided in this study. Cogeneration revenue is also not considered here.

The interest rate in the study is assumed to be 0.06; all costs are calculated in net present value (NPV) of 2010$.

The problem is a LP-based model, which means the investments can be any positive value. Future research will make the investment decision more reasonable by using integer programming or other methods. The real generation expansion problem is much more complicated, and one may refer to the report of EIPC [59] and NREL [60] for more details.

3.2 Nomenclature

The decision variables, indices and parameters are described in this section.

Decision Variables

$x_{y,t,r_1,i}$	Generation amount of generation type i in region r_1 in time period t in year y (MWh)
$s_{y,r_1,i}$	Investment amount of generation type i in region r_1 in year y (MW)

f_{y,t,r_1,r_2} Transmission flow from region r_1 to r_2 in time period t in year y (MWh)

Indices

y Years, alias u

t Time periods in a year

r_1 Regions, alias r_2

i Generation types

n Renewable generation types (subset of i)

e Emission gases

Parameters

r Interest rate

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 gases (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 r_1 at the beginning (MW)

$fnew_{y,r_1,i}$ Forced new capacity of generation type i in region r_1 with online year y (MW)

$fretire_{y,r_1,i}$ Forced retirement capacity of generation type i in region r_1 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)

φ_{y,t,r_1} Demand in region r_1 in time period t in year y (MWh)

$d_{y,t,i}$ Derate 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 r_1 (MW)
m_{y,r_1}	Reserve margin for region r_1 in year y
$MIN_{y,r_1,n}$	Minimum generation percentage requirement of renewable type n for region r_1 in year y
$TMIN_{y,r_1}$	Yearly minimum renewable generation percentage requirement for region r_1 in year y
$EM_{e,i}$	Amount of emission gas e from generation type i (lbs/MWh)
$RLEM_{e,y,r_1}$	Regional limit for emission gas e in region r_1 in year y (lbs)
TL_{y,r_1,r_2}	Transmission limit from region r_1 to r_2 in year y (MW)
$CL_{y,r_1,i}$	Yearly construction limit of generation type i in region r_1 in year y (MW)

3.3 Mathematical Model

The problem is a deterministic linear programming model. The objective is to minimize the net present costs of an expansion planning solution. The total costs include three parts: investment costs of the new construction, electricity generation costs and operation and maintenance costs.

$$\begin{aligned}\min COST = \sum_{y=1}^{Y}\Bigg(\left(1+r\right)^{-y+1}\Bigg(&\sum_{t=1}^{T}\sum_{r_1=1}^{R}\sum_{i=1}^{I}x_{y,t,r_1,i}c_{y,i}+\sum_{r_1=1}^{R}\sum_{i=1}^{I}s_{y,r_1,i}a_{y,i}\\ &+\sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(\sum_{u=1}^{y}\left(s_{u,r_1,i}+fnew_{u,r_1,i}\right)\right)h_{y,i}+\sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(init_{r_1,i}-\sum_{u=1}^{y}fretire_{u,r_1,i}\right)g_{y,i}\Bigg)\Bigg)\end{aligned} \tag{1}$$

s.t.

$$\sum_{i=1}^{I}x_{y,t,r_1,i}-\sum_{r_2=1}^{R}f_{y,t,r_1,r_2}+\sum_{r_2=1}^{R}f_{y,t,r_2,r_1}=\varphi_{y,t,r_1} \qquad \forall y,t,r_1 \tag{2}$$

$$x_{y,t,r_1,i}\le\left(init_{r_1,i}+\sum_{u=1}^{y}\left(s_{u,r_1,i}+fnew_{u,r_1,i}-fretire_{u,r_1,i}\right)\right)cf_{y,t,r_1,i}d_{y,t,i}hours_t \qquad \forall y,t,r_1,i \tag{3}$$

$$\sum_{i=1}^{I}init_{r_1,i}+\sum_{u=1}^{y}\sum_{i=1}^{I}\left(s_{u,r_1,i}+fnew_{u,r_1,i}-fretire_{u,r_1,i}\right)\ge peak_{y,r_1}m_{y,r_1} \qquad \forall y,r_1 \tag{4}$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N} x_{y,t,r_1,n} \geq TMIN_{y,r_1} \sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} \qquad \forall y, r_1 \tag{5}$$

$$\sum_{t=1}^{T} x_{y,t,r_1,n} \geq MIN_{y,r_1,n} \sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} \qquad \forall y, r_1, n \tag{6}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} EM_{e,i} \leq RLEM_{e,y,r_1} \qquad \forall e, y, r_1 \tag{7}$$

$$s_{y,r_1,i} \leq CL_{y,r_1,i} \qquad \forall y, r_1, i \tag{8}$$

$$f_{y,t,r_1,r_2} \leq TL_{y,r_1,r_2} hours_t \qquad \forall y, t, r_1, r_2 \tag{9}$$

$$x_{y,t,r_1,i} \geq 0,\ s_{y,r_1,i} \geq 0,\ f_{y,t,r_1,r_2} \geq 0 \qquad \forall y, t, r_1, r_2, i \tag{10}$$

The objective function (1) is to minimize the net present total costs. Equations (2) state that energy supplies should meet the demands, constraints (3) are capacity constraints, so that generation should not exceed the total capacity, constraints (4) are reserve margin requirements, constraints (5) and (6) represent the RPS requirement. Constraints (7) limit the generation emissions of SO_2, NO_X, and CO_2, while constraints (8) and (9) represent the construction and transmission capacity respectively, and (10) are nonnegative constraints.

3.4 Results

After solving the preliminary model with GAMS/CPLEX, the investment and generation of the optimal solution are shown in Tables 11-12. More details of the optimal solution in this base scenario (Scenario 5) are interpreted in Section 5, when compared to other scenarios. We also make a comparison with the EIPC modeling results. While the majority of the assumptions are the same, we have new emission limits and slightly different generation technologies characteristics. On the other hand, EIPC has considered many more details such as energy efficiency, demand response, energy savings, transmission and trading costs, emission retrofits, etc. Therefore, the results differ in many ways. But we can still observe some similarities in Figures 17-18. To keep consistency with later sections, the base scenario is shown in the blue bar as Scenario 5, and the red bar implies the results of EIPC. It is noted that EIPC uses the term WT as the general onshore wind turbine, which in our model includes WT (existing onshore wind turbine), WT_on3 (new onshore class 3 wind turbine) and WT_on4 (new onshore class 4+ wind turbine). For the ease of comparison, our WT here has the same meaning with EIPC's results.

Table 11 New investments in Scenario 5 (MW)

	CC	CT	LFG	NU	PV	WT	WT_off
2010	43,918	10,387					
2016			489		287	426	
2017			26				
2018			287		622		289
2019					1,485		111
2020					375		507
2021			1	3,750		6,115	
2022			27			5,923	
2023						6,790	
2024						99	
2025						427	
2026			151	8,750			
2030		181					
2031		22		1,423		10,780	

2032	194
2033	196
2034	198
2035	199
2036	201
2037	203
2038	205
2039	206
2040	208

Table 12 Yearly generation in Scenario 5 by technology (GWh)

	CC	Coal	HY	LFG	NU	PS	PV	STOG	WT	WT_off
2010	548,809	0	79,734	1,482	326,734	65,816	137	30,652	21,300	0
2011	558,217	4,271	83,526	8,032	326,734	65,816	204	27,965	28,745	0
2012	556,641	6,198	86,386	10,491	326,288	65,816	288	16,469	37,610	0
2013	554,794	6,848	89,548	10,775	325,913	65,816	288	13,266	41,654	0
2014	554,969	7,417	93,172	10,123	325,591	65,816	288	10,947	43,327	0
2015	557,889	5,218	93,172	9,995	325,313	65,816	288	12,439	44,305	0
2016	550,160	5,639	93,172	16,504	338,189	65,816	1,041	0	46,733	0
2017	554,805	4,183	93,172	15,287	338,189	65,816	1,041	883	46,733	0
2018	552,301	0	93,172	17,800	338,189	65,816	2,676	5,265	46,733	1,047
2019	550,330	0	93,172	16,697	338,189	65,816	6,580	6,961	46,733	1,449
2020	545,599	0	93,172	13,287	338,189	65,816	7,565	15,174	46,733	3,214
2021	505,032	6,838	93,172	24,528	367,414	65,816	7,565	0	61,791	3,214
2022	494,953	8,645	93,172	24,737	367,414	65,816	7,565	0	76,376	3,214
2023	482,185	11,407	93,172	24,737	367,414	65,816	7,565	0	92,948	3,214

2024	492,303	7,689	93,172	24,737	367,414	65,816	7,565	0	93,158	3,214
2025	501,781	4,630	93,172	23,927	367,414	65,816	7,565	0	94,062	3,214
2026	416,709	26,345	93,172	25,928	435,605	65,816	7,565	0	94,062	3,214
2027	427,285	22,510	93,172	25,928	435,605	65,816	7,565	0	94,062	3,214
2028	437,917	18,663	93,172	25,928	435,605	65,816	7,565	0	94,062	3,214
2029	448,605	14,804	93,172	25,928	435,605	65,816	7,565	0	94,062	3,214
2030	459,351	10,934	93,172	25,928	435,605	65,816	7,565	0	94,062	3,214
2031	411,868	23,565	93,172	25,928	446,692	65,816	7,565	0	124,746	3,214
2032	422,729	19,670	93,172	25,928	446,692	65,816	7,565	0	124,746	3,214
2033	433,648	15,762	93,172	25,928	446,692	65,816	7,565	0	124,746	3,214
2034	444,626	11,842	93,172	25,928	446,692	65,816	7,565	0	124,746	3,214
2035	455,663	7,909	93,172	25,928	446,692	65,816	7,565	0	124,746	3,214
2036	466,846	4,495	93,172	25,309	446,692	65,816	7,565	0	124,746	3,214
2037	478,294	2,331	93,172	23,223	446,692	65,816	7,565	0	124,746	3,214
2038	489,804	162	93,172	21,129	446,692	65,816	7,565	0	124,746	3,214
2039	500,598	0	93,172	16,427	446,692	65,816	7,565	1,363	124,746	3,214
2040	507,979	0	93,172	10,705	446,692	65,816	7,565	7,045	124,746	3,214

According to Figure 17, our optimal solution (in blue bar) has the most investments in nuclear, onshore wind turbine and combustion turbine, while EIPC results (in red bar) invest in more in combined cycle. The total investments of our results are significantly larger than EIPC. Note that here in order to compare with results of EIPC, we include the forced new capacity in the investments, while in other sections, we do not generally consider forced new capacity as investment decisions.

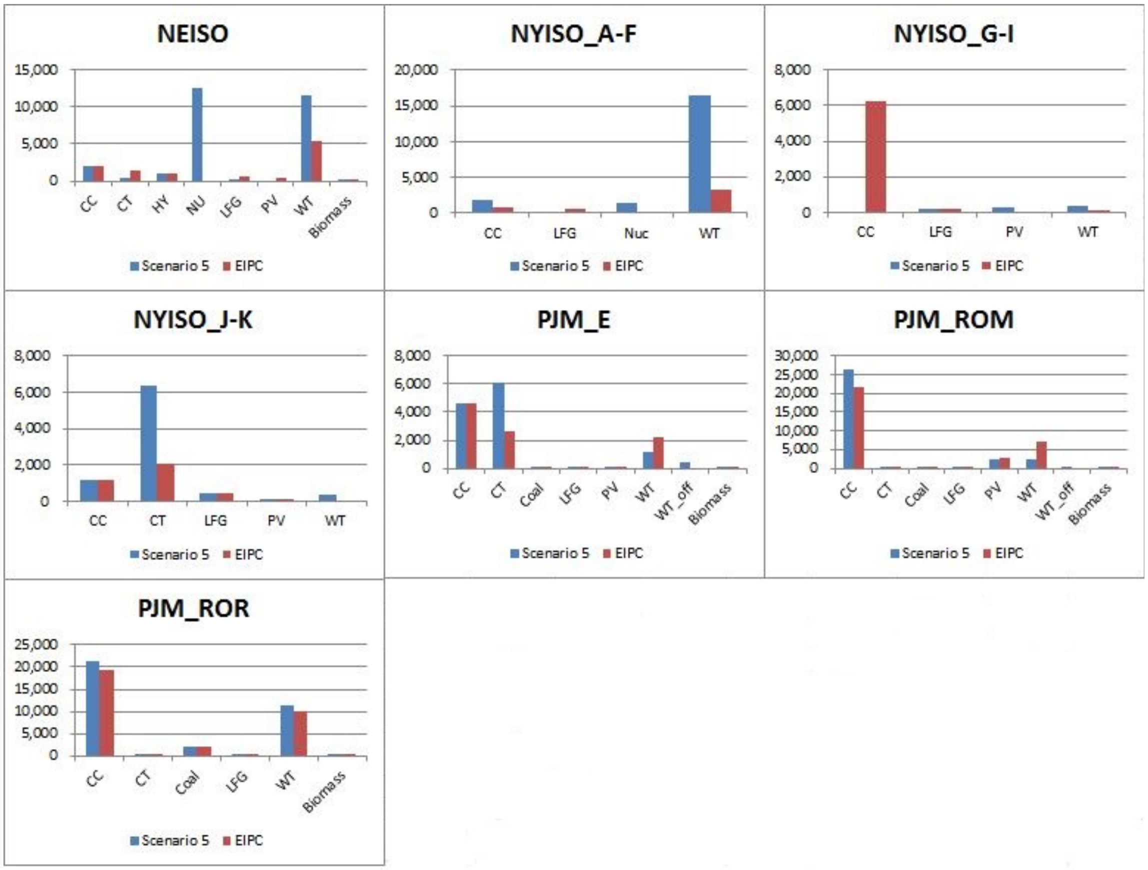

Figure 17 New investments (including forced new capacity) comparison with EIPC by region (MW)

Like the investments, we have much more total generation amount of electricity than EIPC (Figure 18). Similarity lies in the fossil generation, e.g., we both choose combined cycle as the major fossil resources instead of coal. The proportion of coal generation is rather small in both results. But the results are quite different in renewables generation. Our results show significant parts of hydro electricity (including conventional hydro and pumped storage), while EIPC have more biomass, landfill gas and photovoltaic generation.

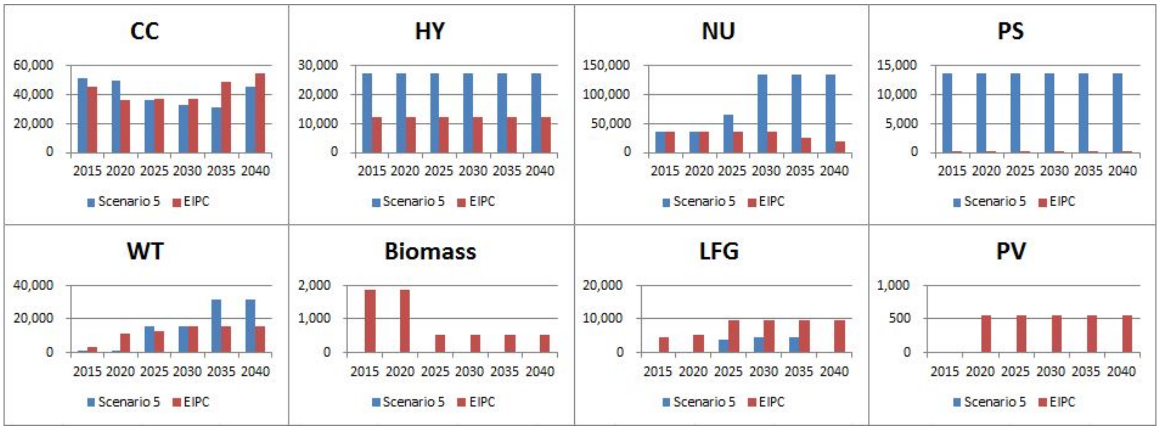

Figure 18 Generation comparison with EIPC in NEISO (GWh)

3.5 Conclusion of Preliminary Model

We introduce our preliminary GEP model with results compared to EIPC. GEP models have been well developed in the past years, therefore, the mathematical models in literature share objectives and a lot of constraints in common. Our model is one of those models that have single objective least cost and a wide range of constraints. The preliminary model is a large-scale linear programming problem, in which the collected data and output are stored in corresponding excel files.

Carefully designed cases have been tested to validate the model, however, our results are still dissimilar to the results of EIPC. EIPC and NREL have been working on the generation expansion planning problems for systematically and collaboratively in much more detail for years. Although most of our data comes from EIPC assumptions, our model is much more simplified and theoretical. Future research should continuously improve the mathematical model by including more realistic constraints and data.

4 Climate Variables

In this section, three major climate variables relevant to the power system are introduced. In the Northeast region, temperature and precipitation are projected to increase with seasonal variation; the frequency and intensity of extreme events are projected to increase. In general, increasing temperature, decreasing precipitation and increasing extreme events will reduce the capacity of electric power generation system, as shown in Table 13. We refer to a wide range of literature to identify how the climate change will affect different sectors of the power system, and then come up with our definition of the quantifiable impacts. They are important inputs when we generate the climate scenarios, as well as relate the scenarios variables to the GEP models parameters.

Table 13 Relationship between climate change projections and implications for GEP parameters

Climate change trend	Impact	GEP parameters	Implication
Increasing temperature	Electricity generation	Generation capacity factors (Coal, CT, CC, GEO, LFG, NU, ST, STOG, STWD, IGCC, IGCC_seq, AC, Biomass)	Reducing thermal efficiencies
		PV capacity factor	Reducing efficiency of the semiconducting material
	Power grid	Transmission loss	Decreasing transmission capacity
	Electricity demand	Demand	Lower heating demand, higher cooling demand
		Peak demand	Higher peak demand
Decreasing precipitation	Electricity generation	Generation capacity factors (CT, CC, GEO, LFG, NU, ST,	Decreasing cooling water for thermal generation

		STOG, STWD, IGCC, IGCC_seq, AC, Biomass)	
	Hydropower	Hydropower capacity factor	Decreasing streamflow
Increasing frequency and intensity of extreme events (storm, flooding, heat wave, wildfire)	Electricity generation	Derate rate	More storms and flooding and potential wear
	Power grid	Transmission loss	Storms/wildfire damage
	Electricity demand	Reserve margin	Reliability requirement
		Peak demand	Extreme heat wave

4.1 Temperature

Temperatures across the United States have increased during the past 100 years and will continue increasing in the future. Increasing temperature has an impact on electricity demand, generation capacity and transmission capacity. The National Oceanic and Atmospheric Administration projects the Northeastern region average temperature increases of 3.0°F by 2035, 4.8°F by 2055, and 8.0°F by 2085 for the high (A2) emissions scenario, and for the low (B1) emissions scenario, of 2.7°F by 2035, 3.6°F by 2055, and 4.7°F by 2085, with respect to 1971-1999 [40].

Figure 19 illustrates the simulated differences in annual mean temperature under each emission scenario; Figure 20 shows the seasonal variations under a higher emission scenario. Based on the simulation for Northeastern region, some temperature variables simulations under higher emissions scenario (A2) are shown in Table 14.

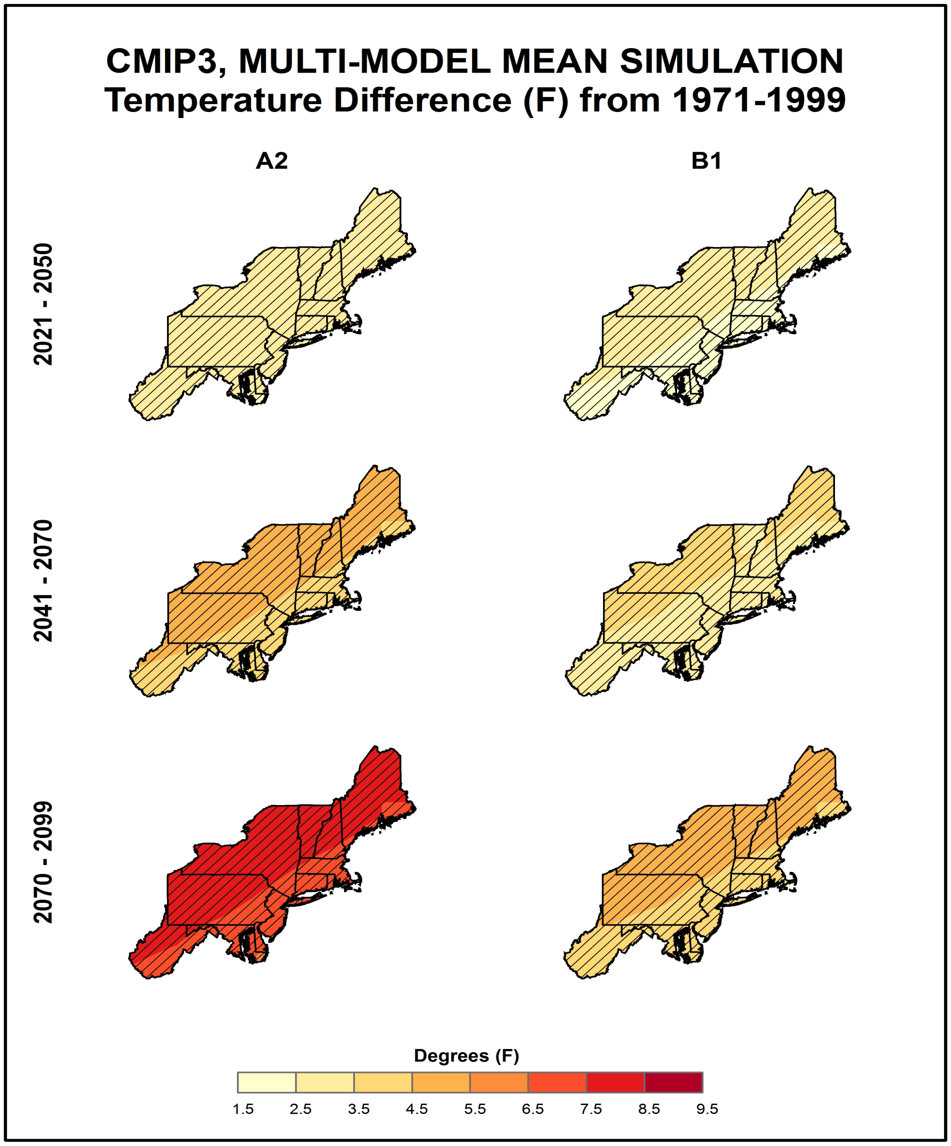

Figure 19 simulated differences in annual mean temperature (°F) for the Northeast region, with respect to the reference period of 1971-1999 [40]

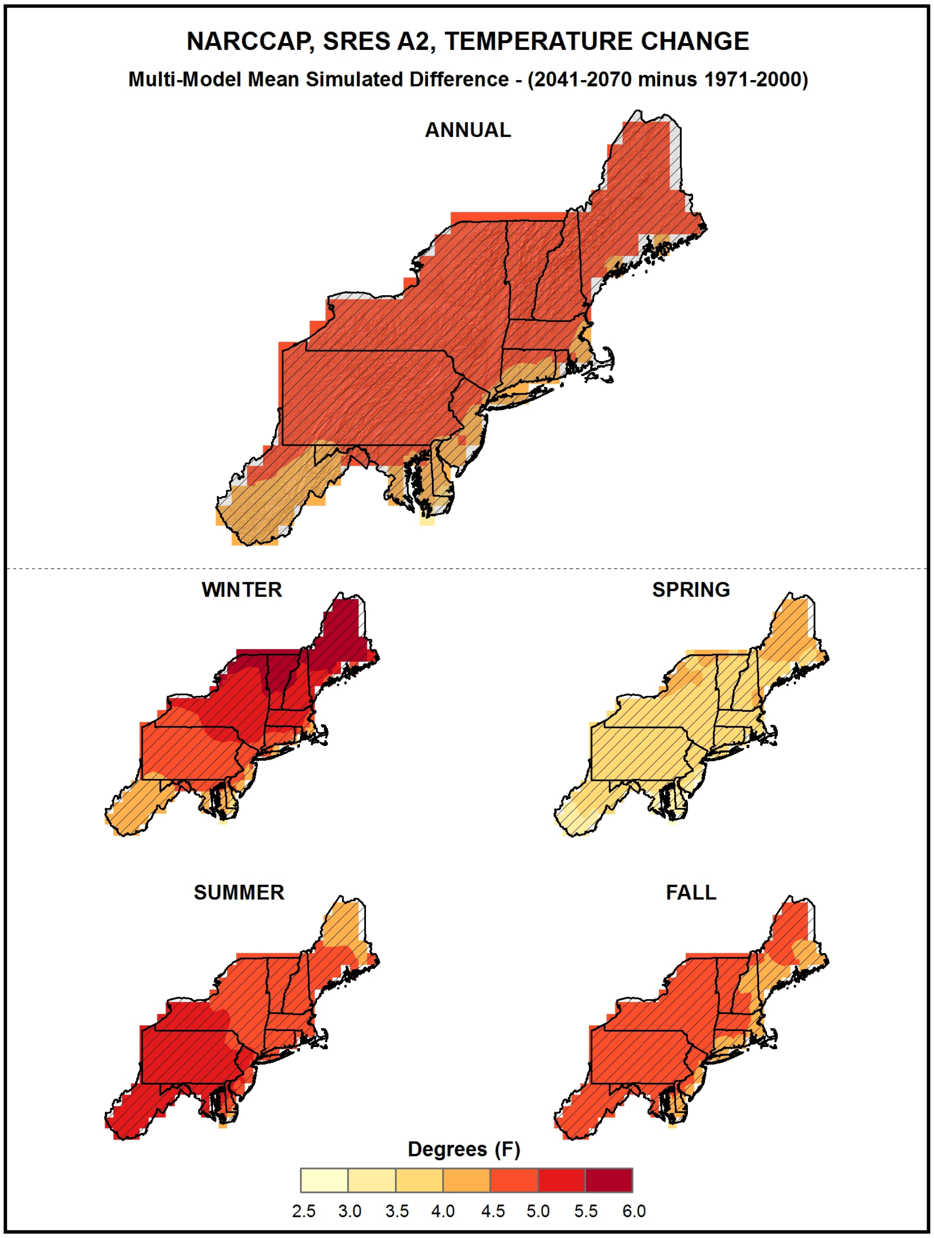

Figure 20 Simulated differences in annual and seasonal mean temperature (°F) for the Northeast region, for 2041-2070 with respect to the reference period of 1971-2000 under a higher (A2) emissions scenario [40]

Table 14 Annual mean change in selected temperature variables from NARCCAP simulations for Northeastern region, 2041-2070 with respect to 1971-2000, under higher emissions scenario (A2)

Temperature Variable	NARCCAP Simulation Mean

Freeze-free period	+26 days
#days *Tmax* > 90°F	+13 days
#days *Tmax* > 95°F	+8 days
#days *Tmax* > 100°F	+4 days
#days *Tmin* < 32°F	-26 days
#days *Tmin* < 10°F	-17 days
#days *Tmin* < 0°F	-9 days
Consecutive #days > 95°F	+171%
Consecutive #days > 100°F	+237%
Heating degree days	-16%
Cooling degree days	+99%
Growing degree days (base 50°F)	+41%

Source: North American Regional Climate Change Assessment Program (NARCCAP) [40]

4.1.1 Projections

Increasing ambient air and water temperatures are projected to increase steam condensate temperatures and turbine backpressure, reduce the thermal efficiencies of thermoelectric power plants. This will reduce the output of natural gas, coal, nuclear, solar thermal, biomass, and geothermal power plants. For example, the power output of natural gas-fired combustion turbines is estimated to decrease by approximately 0.6%-0.7% for a 1°C increase in air temperature [44]. For combined cycle power plants, output can decrease by approximately 0.3%-0.5% for 1°C increase in air temperature [45]. For nuclear power plants, output is estimated to decrease by approximately 0.45%-0.5% for a 1°C increase in air temperature [46, 63].

Increasing temperature could reduce the generation capacity of solar photovoltaic because of the semiconducting material. One of the studies shows the output of a crystalline silicon PV cell decreases by about 0.65% per 1°C increase in air temperature [47]. Temperature also has an effect on other renewable resources, wind, hydropower, but these projection remain uncertain due to many other factors, such as various wind patterns and river stream.

As temperature increases, the transmission losses increase. A study of the California electricity system shows that a 5°C air temperature increase diminishes the capacity of a fully loaded transmission line by an average of 7.5% [48].

Demand and peak demand are often modeled as a function of different temperature variables. As temperature increases, heating demand will decrease, and cooling demand will increase. The increasing frequency and duration of heat wave will lead to higher peak demand. Overall, electricity demand is projected to increase since demand for cooling is primarily supplied by electricity, while demand for heating is supplied by a variety of energy sources, including natural gas, heating oil, and electricity [51].

However, temperature is not the only factor that affects electricity demand; population, economic conditions, energy prices, consumer behavior and many other factors are considered when predicting the demand and peak demand. Therefore, multiple projections are needed due to uncertainty, for example, a study in California shows that by midcentury, residential peak demand is projected to increase by 2.8%-7.7% under a lower emissions scenario (B1) and by 3.4%-10.0% under higher emissions scenarios (A2 and A1FI) compared to the average demand of 1961-1990 [41]. Another study of electricity demand in California uses different models for projection in the CalISO area. The estimated increases in annual electricity and peak load in downscaling Parallel Climate Model (PCM, lower-sensitivity model) of the National Center of Atmospheric Research (NCAR) and Geophysical Fluid Dynamics Laboratory global circulation model (GFDL, higher-sensitivity model) are shown in Table 15 [18].

Table 15 Estimated increases in annual electricity and peak load demand, relative to the 1961-1990 base period [18]

Climate Model	Year	Emissions Scenario	Annual Electricity (%)	Peak Demand (%)
PCM	2005-2034	A2	1.2	1.0
Projected end of century		B1	0.9	1.4
warming [50]	2035-2064	A2	2.4	2.2
A2: 2.6°C		B1	1.7	1.5
B1: 1.7°C	2070-2099	A2	5.3	5.6
		B1	3.1	4.1
GFDL	2005-2034	A2	2.9	3.6
Projected end of century		B1	2.5	4.1
warming [50]	2035-2064	A2	5.0	5.0
A2: 3.9°C		B1	4.2	5.0
B1: 2.2°C	2070-2099	A2	11.0	12.1
		B1	5.8	7.3

In addition to the annual electricity demand increasing projection, some studies have also examined seasonal variations. In one study of the Northwest, the projected change of demand is greater in the summer than the winter. Summer demand is approximately projected to increase by 4.7% due to a 1.6°C increase in summer temperature, whereas winter demand is approximately projected to decrease by 2.5% due to a 1.1°C increase in winter temperature [34].

4.1.2 Assumptions

Based on the projections from different references, Table 16 gives the summary of temperature impact on GEP paramters. It is assumed that the correlations between temperature and GEP parameters are linear. Major impacts are considered and defined, while unclear and negligible impacts are omitted.

Table 16 Magnitude of impact from temperature on GEP parameters

	GEP Parameters	Impact
Temperature (+1°C)	Capacity factor	Coal, STOG, STWD, AC (-0.1%)
		CT (-0.65%)
		CC, IGCC, IGCC_seq (-0.4%)
		GEO, LFG, Biomass (-0.1%)
		PV, ST (-0.65%)
		NU (-0.5%)
	Transmission capacity	(-1.5%)
	Annual demand	(+2.2%)
	Summer demand	(+2.7%)
	Winter demand	(-2.3%)
	Peak demand	(+2.9%)

4.2 Precipitation

The cooling water availability will be impacted by a change pattern of precipitation, streamflow, runoff and snowpack, among which precipitation is a major cause. It is projected that for the Northeastern region, the annual mean precipitation will increase, with regional and seasonal variations [40]. The Northeast has observed increasing precipitation, streamflow, runoff, reduction in snowpack whereas the precipitation and streamflow are projected to decrease in the Southwest [51]. According to National Oceanic and Atmospheric Administration (NOAA) simulation, although annual precipitation of the Northeast is going to increase (Figure 21) but in a higher emissions scenario, the summer precipitation will decrease (Figure 22), which will limit the available summer capacity of generation due to less availability of cooling water and reduce hydroelectric power output.

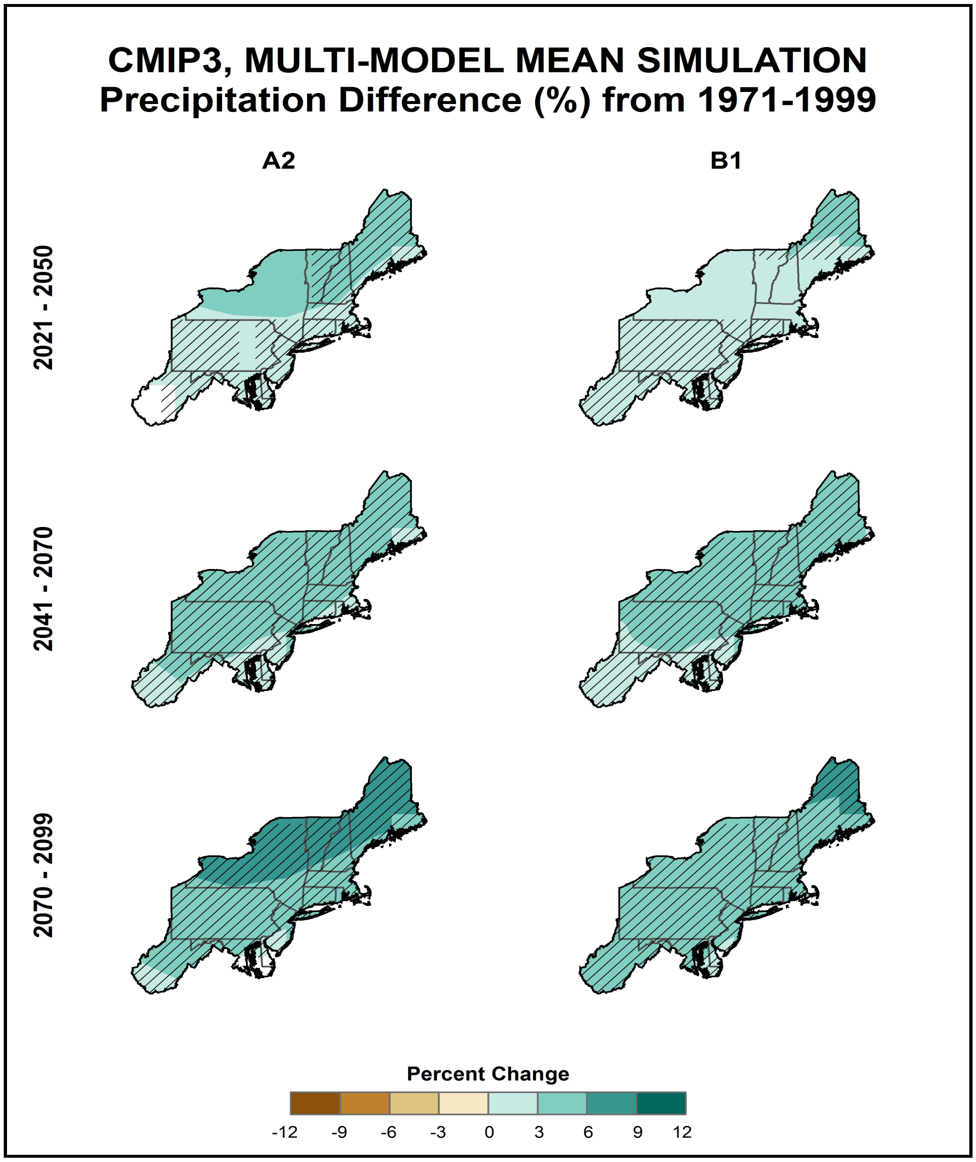

Figure 21 Simulated differences in annual mean precipitation (%) for the Northeast region, with respect to the reference period of 1971-1999 [40]

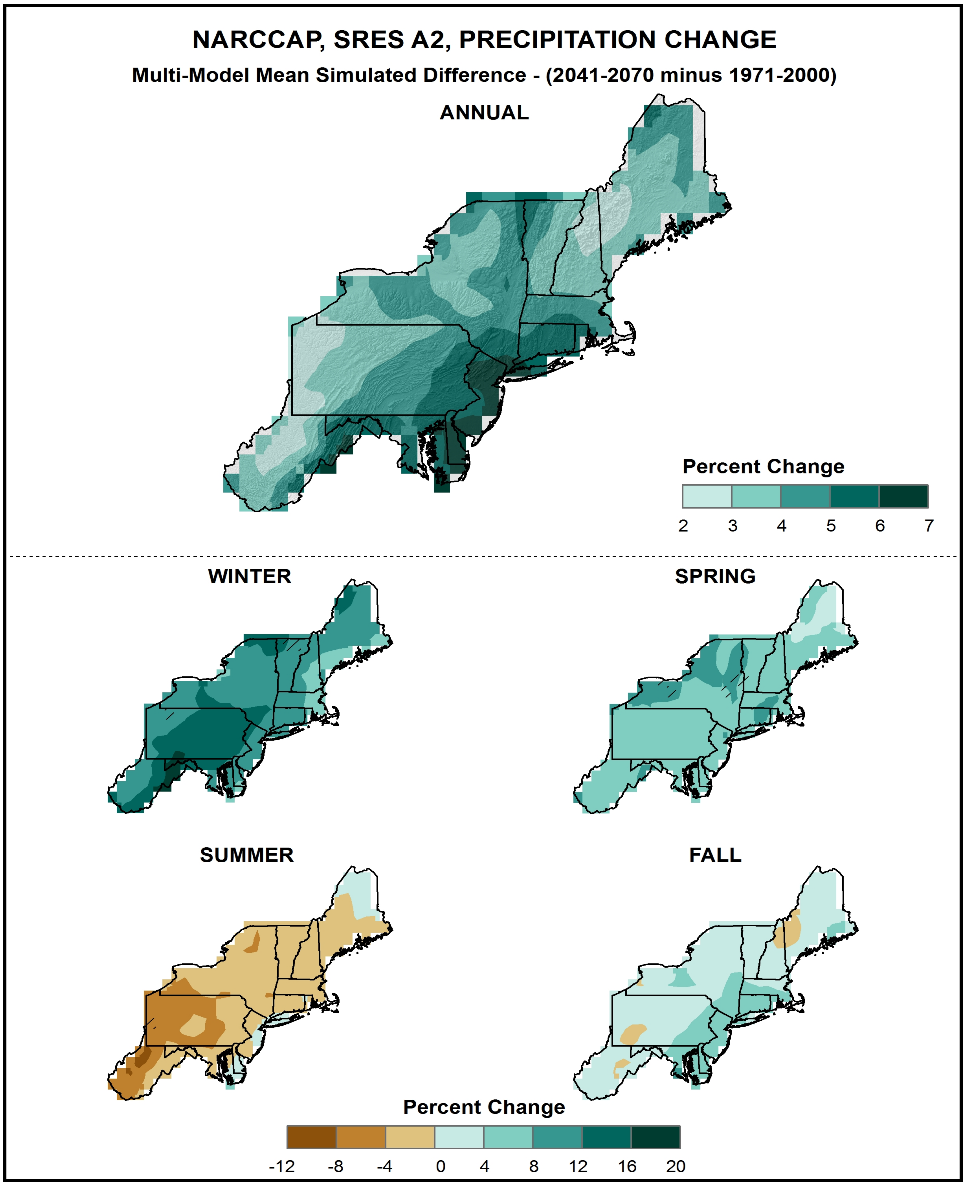

Figure 22 Simulated differences in annual and seasonal mean precipitation (%) for the Northeast region, for 2041-2070 with respect to the reference period of 1971-2000 under a higher (A2) emissions scenario [40]

4.2.1 Projections

Approximately 90% of thermoelectric power generation in the United States requires water for cooling, and once-through cooling systems are particularly vulnerable to low streamflow conditions due to the large volumes of water withdrawn [36]. Steam-cycle coal-fired power plants typically use more water than steam-cycle natural gas-fired power plants. Combined cycle plants are more water-efficient. Nuclear power plants, solar thermal plants, and geothermal plants can withdraw and consume as much, or more, freshwater as fossil-fueled thermoelectric facilities [52]. In contrast, relatively little water is consumed in the generation of electricity from solar photovoltaic or wind technologies [36].

According to a recent estimation study estimation of US, the summer average available capacity of power plants with once-through and recirculating cooling systems is projected to decrease by 12%-16% and 4.4%-5.9% respectively, for the period 2031-2060, compared to 1971-2000 [53].

Hydroelectric generation is very sensitive to changes in precipitation and river discharge. For example, every 1% decrease in precipitation results in a 2-3% percent drop in streamflow; while every 1% decrease in streamflow in the Colorado River Basin results in a 3% drop in power generation [51].

4.2.2 Assumptions

Linear correlations are assumed between the precipitation and GEP parameters. Major impacts are considered and defined in Table 17, while unclear and negligible impacts are omitted.

Table 17 Magnitude of impact from precipitation on GEP parameters

	GEP Parameters	Impact
Precipitation (-1%)	Capacity factor	Coal, CT, STOG, STWD, AC (-2.5%)
		CC, IGCC, IGCC_seq (-0.8%)
		NU, ST, GEO, LFG, Biomass (-3%)
		HY (-6%)

4.3 Extreme Events

Since the 1970s, the intensity of hurricanes and tropical storms has increased and is likely to increase in the future [39]. One study projects nearly a doubling of the frequency of category 4 and 5 storms by the end of the 21st century, despite a decrease in the overall frequency of tropical cyclones, as shown in Figure 23 [55].

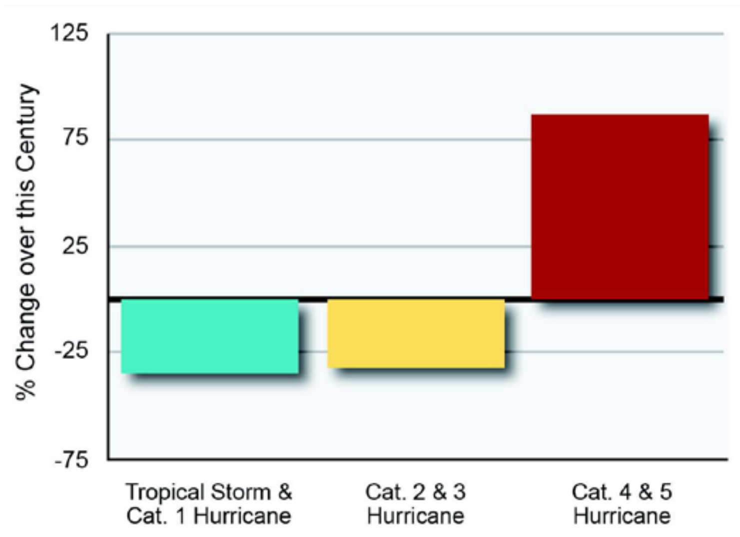

Figure 23 Projected changes in Atlantic hurricane frequency by category for 2081-2100, with respect to 2001-2020 [36]

In the future, more frequent and intense downpours and a greater proportion of total rainfall coming from heavy precipitation events are very likely across the United States [32]. Historical data in Figure 24 shows an increasing trend of very heavy precipitation events, especially in the Northeast. Measurements of stream gauges with at least 85 years of historical records show that the greatest increases in peak streamflows have occurred in the upper Midwest (specifically, the Red River of the North), and in the Northeast (especially in eastern Pennsylvania, New York, and New Jersey) [54].

In general, areas that are projected to receive the greatest increases in heavy precipitation are also expected to experience greater flooding, such as the Northeast and Midwest, with some uncertainty [36]. Projections indicate that it is likely that a 1-in-20 year annual maximum 24-hour precipitation rate will become a 1-in-5 to 1-in-15 year event by the end of 21st century in many regions (A2, A1B, and B1 emission scenarios) [39].

At the same time, all regions of U.S. are very likely to experience an increase in maximum temperature as well as an increase in frequency and intensity of heat wave [51]. It is assessed that a 1-in-20 year annual extreme hot day is likely to become a 1-in-2 year annual extreme by the end of the 21st century in most regions (A2 and A1B higher emission scenarios), and is likely to become a 1-in-5 year annual extreme (B1 lower emission scenario) [39].

Due to large uncertainty in the data collection and modeling, although regional and global studies indicate an increasing trend of droughts, floodings and extreme sea level rise, there is low confidence in those projections [39].

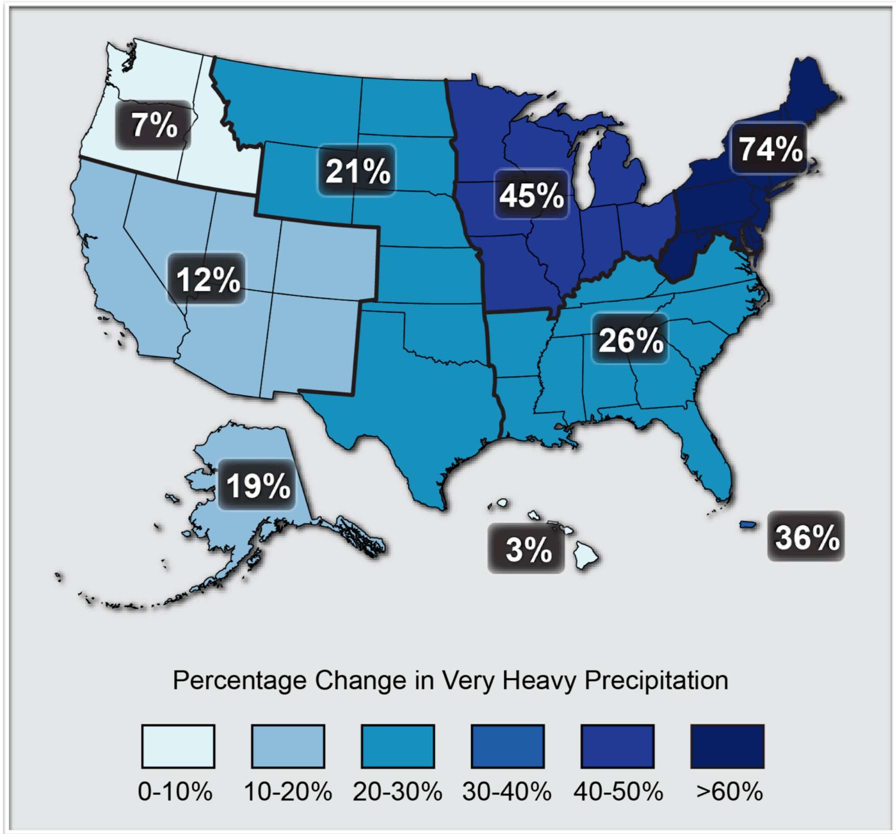

Figure 24 Percent increases in the amount of precipitation falling in very heavy events (defined as the heaviest 1% of all daily events) from 1958 to 2011, with respect to 1901-1960 [49]

4.3.1 Projections

Extreme events can lead to major interruption of energy and economic loss. For example, in 2012, storm surge and high winds from Hurricane Sandy downed power lines, flooded substations and underground distribution systems, and damaged or temporarily shut down ports and several power plants in the Northeast, including eight nuclear power units in the region [56]. During a 2006 heat wave, electric power transformers failed in Missouri and New York, causing interruptions of the electric power supply [51].

Hurricanes and storms can disrupt the costal facilities while the floodings cause the shutdown of inland facilities. Extreme events will likely result in increasing transmission loss and even damage of power grid. However, there are no accurate projections related to the weather disasters and power generation system.

4.3.2 Assumptions

Linear correlations are assumed between the extreme events and GEP parameters. Major impacts are considered and defined in Table 18, while unclear and negligible impacts are omitted.

Table 18 Magnitude of impact from extreme events frequency on GEP parameters

	GEP Parameters	Impact
Frequency (+100%)	Derate rate	Maintenance time (+20%)
	Transmission capacity	(-3%)
	Reserve margin	(+10%)
	Peak demand	(+5%)

4.4 Conclusion of Climate Variables

The projections of temperature, precipitation, extreme events as well as their impacts on the electric power generation system are briefly discussed in this section. Appropriate assumptions are included. We assume that the relationship between climate variables and GEP parameters are linear, while it is not in most real cases. Uncertainty assumptions and the experts' projections mentioned here are subjected to spatial and temporal conditions, for example, there are many studies forecasting the electricity demands for California, but not many for the Northeast area. For the extreme events, few climate models can have high confidence of future predictions. Therefore, due to the complexity and uncertainty, consistency of data and projections from various literature are not considered in this study. We simply take their results along with our assumptions as the theoretical input. Further studies can focus on the data and possibly propose sensitivity analysis for each of the climate variables.

5 Scenarios

Each scenario is a realization of a set of random variables over the planning horizon. In this research, discrete climate scenarios with a set of climate variables are defined. Climate variables are related to the GEP model parameters through the method described in Section 4. Therefore, each climate scenario corresponds to a scenario of uncertain GEP parameters. After introducing the definition of scenarios considered in the research, we present the optimal electric power generation expansion planning solution under each scenario using the preliminary model in Section 3. Therefore, by comparing the optimal solutions between scenarios, the impact of climate change on the generation expansion decision can be identified.

5.1 Definition of Scenarios

Each climate scenario has three major climate variables: temperature, precipitation and extreme events as shown in Table 19, and corresponds to six sets of GEP parameters: demand, peak demand, capacity factor, transmission capacity, reserve margin and derate rate. Based on the results of [32, 33, 36, 37, 39, 40, 49, 50, 51, 53], we assume that temperature is going to increase equally in different seasons (the literature shows little seasonal variation), whereas annual and summer precipitations are defined separately (summer precipitation is largely distinguished from annual precipitation). Only the frequency of extreme events is included in the scenarios, since intensity and duration are difficult to model and project. It is noted that temperature and precipitation of Scenarios 2 and 3 are extracted from experts' projections of higher and lower emissions scenarios.

Table 19 Climate scenarios summary by 2035, with respect to 1971-2000

Scenario	Temperature	Precipitation		Extreme events
	Annual	Annual	Summer	Frequency
1	+4.4°C	+12%	-4%	+300%
2	+1.7°C	+4%	+1%	+75%
3	+1.5°C	+3%	+2%	+50%
4	+1.0°C	+2%	+0%	+10%
5	As present	As present	As present	As present

We have discussed the inputs and assumptions in Section 3. It is noted that those assumptions are made without considering the impact of climate change. In other words, those assumptions are used in Scenario 5, which is the base scenario with every climate variable remaining the same in the fifty-year range.

As we define Scenarios 1-4 differing on the extent of climate change, whereas most of the non-climate-related GEP parameters are not changed, the six sets of climate-related GEP parameters are affected, which are summarized in Table 20. By comparing with the parameters in Scenario 5, Table 20 provides the additional yearly growth rate due to climate change. For example in Scenario 5, the peak demand growth rate of NEISO from 2010 to 2020 is 0.49% as listed in Table 3. Thus the peak demand growth rate NEISO from 2010 to 2020 is (0.49%+0.56%=1.05%) in Scenario 1.

Table 20 Additional yearly growth rates for each scenario due to climate change, with respect to Scenario 5

	Scenario	1	2	3	4
Additional demand growth	Summer	+0.24%	+0.092%	+0.081%	+0.054%
	Shoulder (spring/fall)	+0.19%	+0.075%	+0.066%	+0.044%

	Winter	-0.2%	-0.078%	-0.069%	-0.046%
Additional peak demand growth		+0.56%	+0.175%	+0.137%	+0.068%
Additional reserve margin requirement		+0.6%	+0.15%	+0.1%	+0.02%
Additional maintenance time		+1.2%	+0.3%	+0.2%	+0.04%
Additional transmission loss		+0.31%	+0.096%	+0.075%	+0.036%
Additional summer capacity factor decrease	Coal, STOG, STWD, AC	-0.209%	-	-	-
	CT	-0.257%	-	-	-
	CC, IGCC, IGCC_seq	-0.099%	-	-	-
	GEO, LFG, Biomass	-0.249%	-	-	-
	PV	-0.057%	-	-	-
	NU	-0.284%	-	-	-
	ST	-0.297%	-	-	-
	HY	-0.48%	-	-	-
Additional shoulder (spring/fall) and winter capacity factor decrease	Coal, STOG, STWD, AC	-0.009%	-0.003%	-0.003%	-0.002%
	CT	-0.057%	-0.022%	-0.02%	-0.013%
	CC, IGCC, IGCC_seq	-0.035%	-0.014%	-0.012%	-0.008%
	GEO, LFG, Biomass	-0.009%	-0.003%	-0.003%	-0.002%
	NU	-0.044%	-0.017%	-0.015%	0.01%
	PV	-0.057%	-0.022%	-0.02%	-0.013%
	ST	-0.057%	-0.022%	-0.02%	-0.013%

5.2 Optimal Solution under Each Scenario

GAMS/CPLEX is used to solve the deterministic linear programming of the preliminary model. The optimal solutions are graphed and analyzed after we solve the preliminary models with sets of parameters corresponding to the scenarios.

5.2.1 Expansion Costs

The expansion costs under each scenario are shown in Table 21. As we defined earlier, Scenario 5 is the base scenario, in which climate will remain the same as present for the next thirty years. Therefore, the additional expansion costs under other scenarios are compared to Scenario 5, which implies the climate change effects. Scenario 1, which is the most extreme scenario, has the most climate change effects, which is about 5% more than no climate change scenario, equivalent 45 Billion in 2010 dollars. Tables 22 and 23 provide the corresponding effects in investments and generation due to climate change.

Table 21 Total expansion cost in each scenario 2010-2040

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Expansion cost (2010$ Billion)	968.06	934.85	932.97	929.18	923.61
Climate change cost (2010$ Billion)	44.45	11.24	9.36	5.57	0.00
Climate change effect	4.81%	1.22%	1.01%	0.60%	0.00%

5.2.2 New Investments

The investments are the decision variables, which decide the type and amount of capacity that is constructed every year in every region. Table 22 shows that Scenario 1 has 45% more investments than Scenario 5, which implies under the most extreme scenario, climate change results in almost 50% more capacity investments. It is because Scenario 1 has the largest demand increasing and capacity decreasing, while the emission limits and Renewable Portfolio Standards requirements are not relaxed.

Table 22 Total investments in each scenario 2010-2040

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Total investments (MW)	153,073	115,565	112,581	108,828	105,457
Climate change effect (MW)	47,617	10,108	7,124	3,371	0
Climate change effect	45.15%	9.59%	6.76%	3.20%	0.00%

Figure 25 depicts the total investments in different regions during the planning horizon 2010-2040. The extreme scenario has the most investments, most of which occur in the PJM_ROR region. It means that PJM_ROR can provide relatively inexpensive investments in the case of extreme climate change.

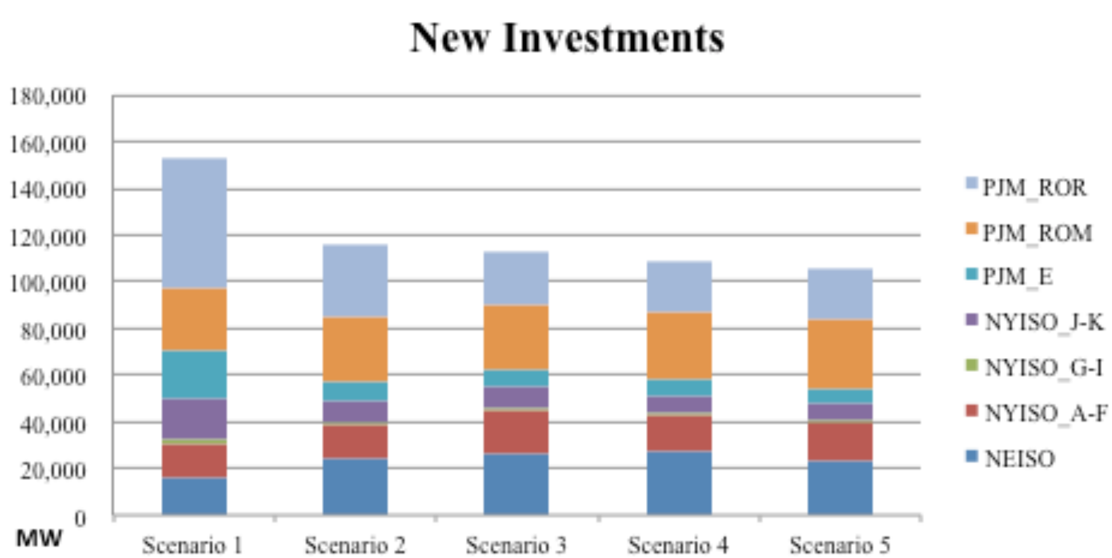

Figure 25 Total investments in each region in each scenario 2010-2040 (MW)

From Figures 26-27, the five scenarios share the same varieties of investments: combined cycle, combustion turbine, landfill gas, nuclear, photovoltaic, onshore wind turbine (class 3 and class 4+ wind) and offshore wind turbine, but slightly differ in the investment amounts. The extreme case Scenario 1 has significantly more investments during 2021-2025, and onshore wind turbine takes the largest portion, which indicates that onshore wind turbine is invested to combat extreme climate change given forced emission limits.

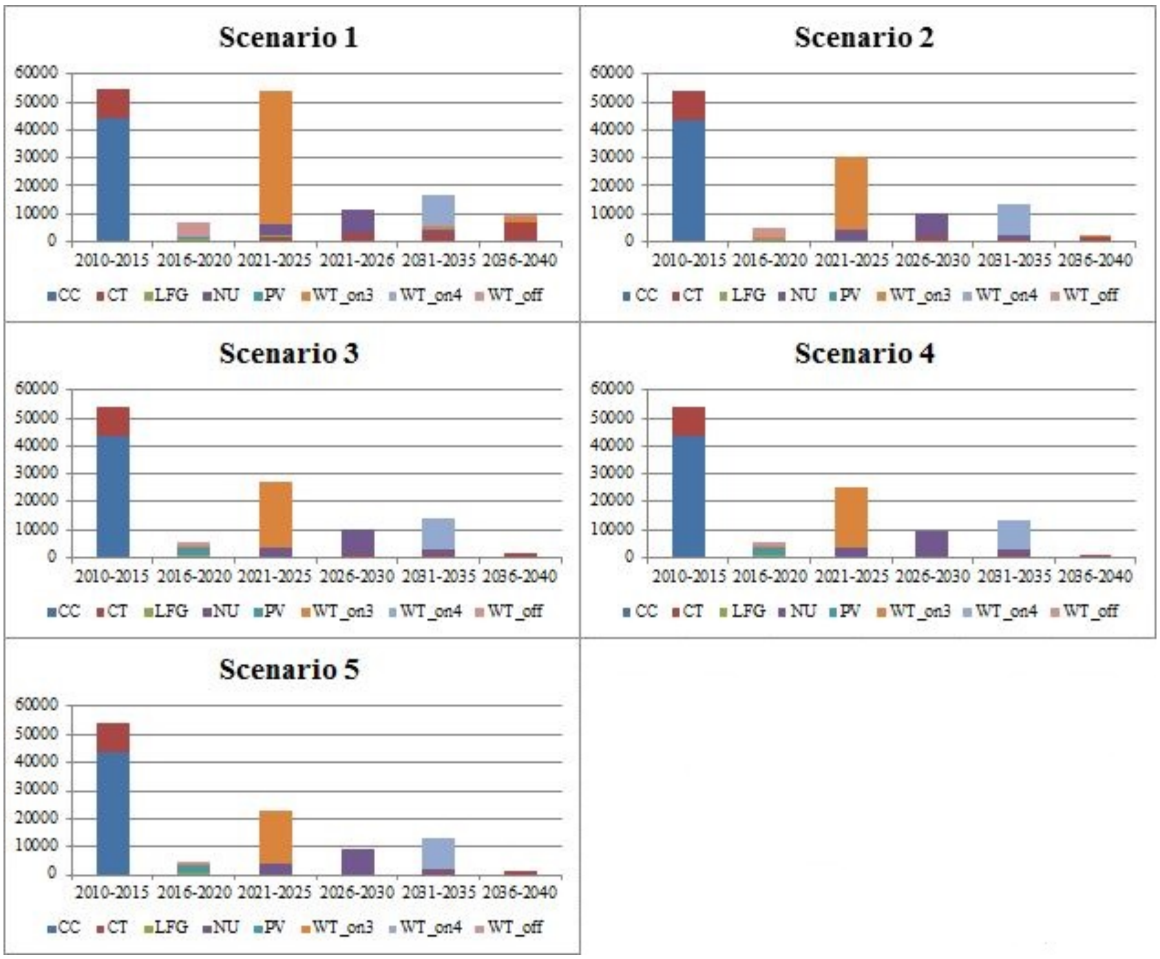

Figure 26 New investments in each scenario (MW)

Figure 27 indicates that except for onshore wind turbine, combustion turbine is also invested more extensively in case of higher peak demand, while combined cycle has a smaller portion of total investments as climate becomes more extreme. The reason is that combustion turbine has a lower capital cost.

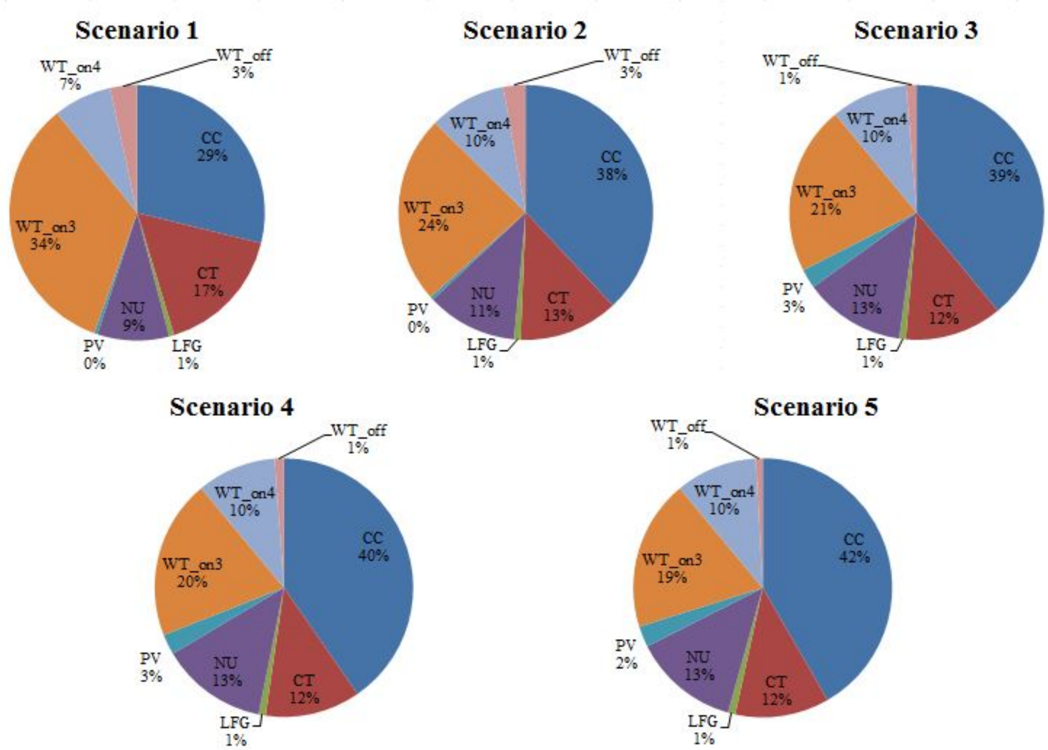

Figure 27 Proportion of total investments by technology in each scenario (2010-2040)

5.2.3 Generation

In terms of the generation, the total generation in each scenario is listed in Table 23. Unlike investments, Scenario 1 only has 1.82% more generation when compared to Scenario 5, which implies that more investments should be planned even though the demands are not significantly increasing.

Table 23 Total generation in each scenario 2010-2040

	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Total generation (1000 GWh)	36,919	36,507	36,477	36,403	36,258
Climate change effect (1000 GWh)	661	249	219	145	0
Climate change effect	1.82%	0.69%	0.60%	0.40%	0.00%

As shown in Figure 28, fossil resources generation is gradually replaced by generation from renewable resources across all scenarios. Especially in the most extreme scenario, the average generation proportion of renewables is the largest. That is because given the same emission limits for all scenarios, more demand and generation is correlated with less fossil generation. For the renewables generation percentage in Figures 29-30, onshore wind turbine is gradually replacing hydro-electricity. It is interesting to observe that combustion turbine has been invested in a large amount but not heavily utilized for generation, because of expensive operation costs. Therefore, it is good to keep combustion turbine as peaker generation units or to meet reserve margin reliability requirements.

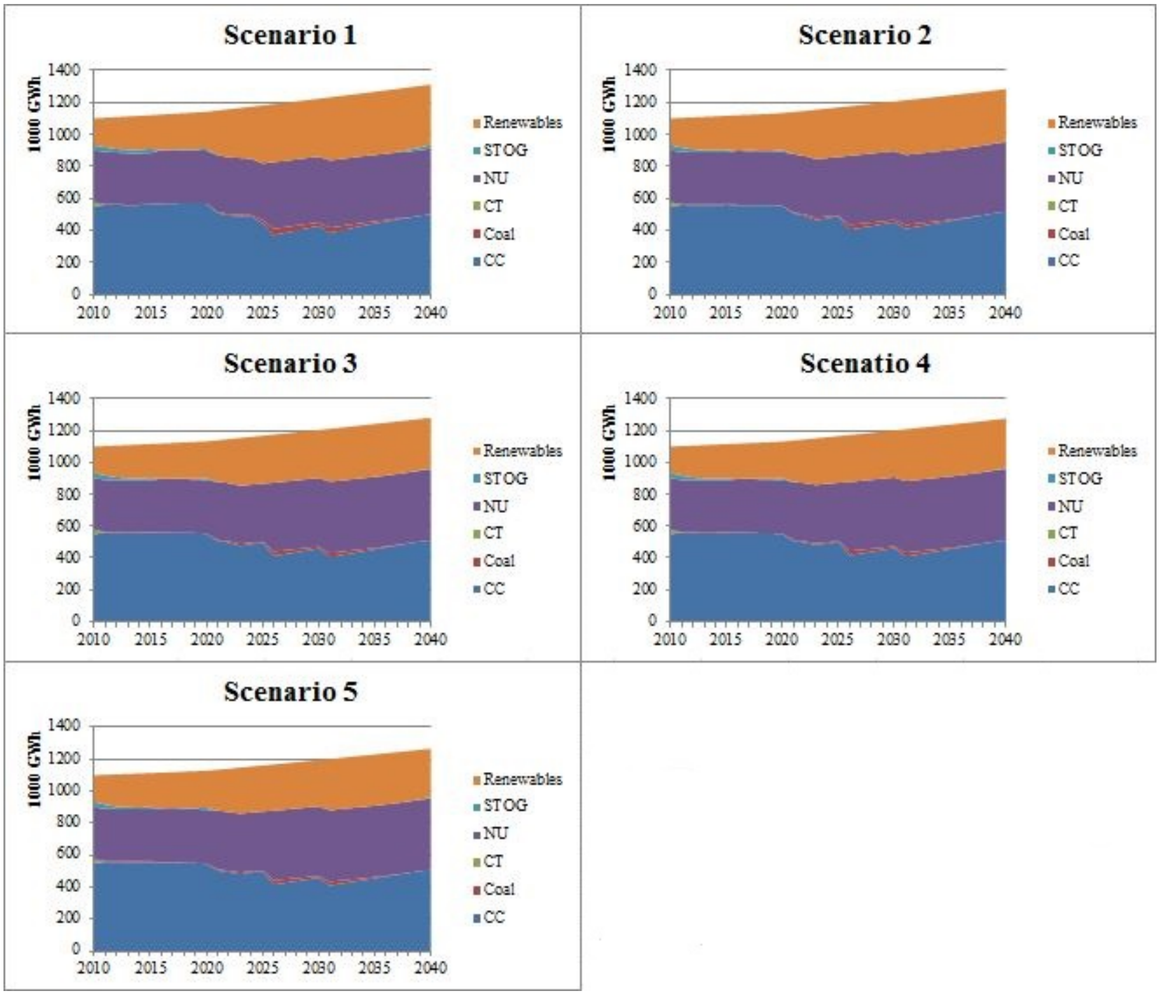

Figure 28 Generation in each scenario 2010-2040 (1000GWh)

In our results (Figures 29-30), coal is taking 1% of the generation across all scenarios, which is similar to EIPC's results [59]. Previously in Section 2.2 Figure 11, we have mentioned that coal is and will remain an important source of electricity generation. Our results here do not exactly match the reality (coal is one of our primary resources nowadays) because of emission limits. However, once we relax the bound of emission, coal generation increases dramatically.

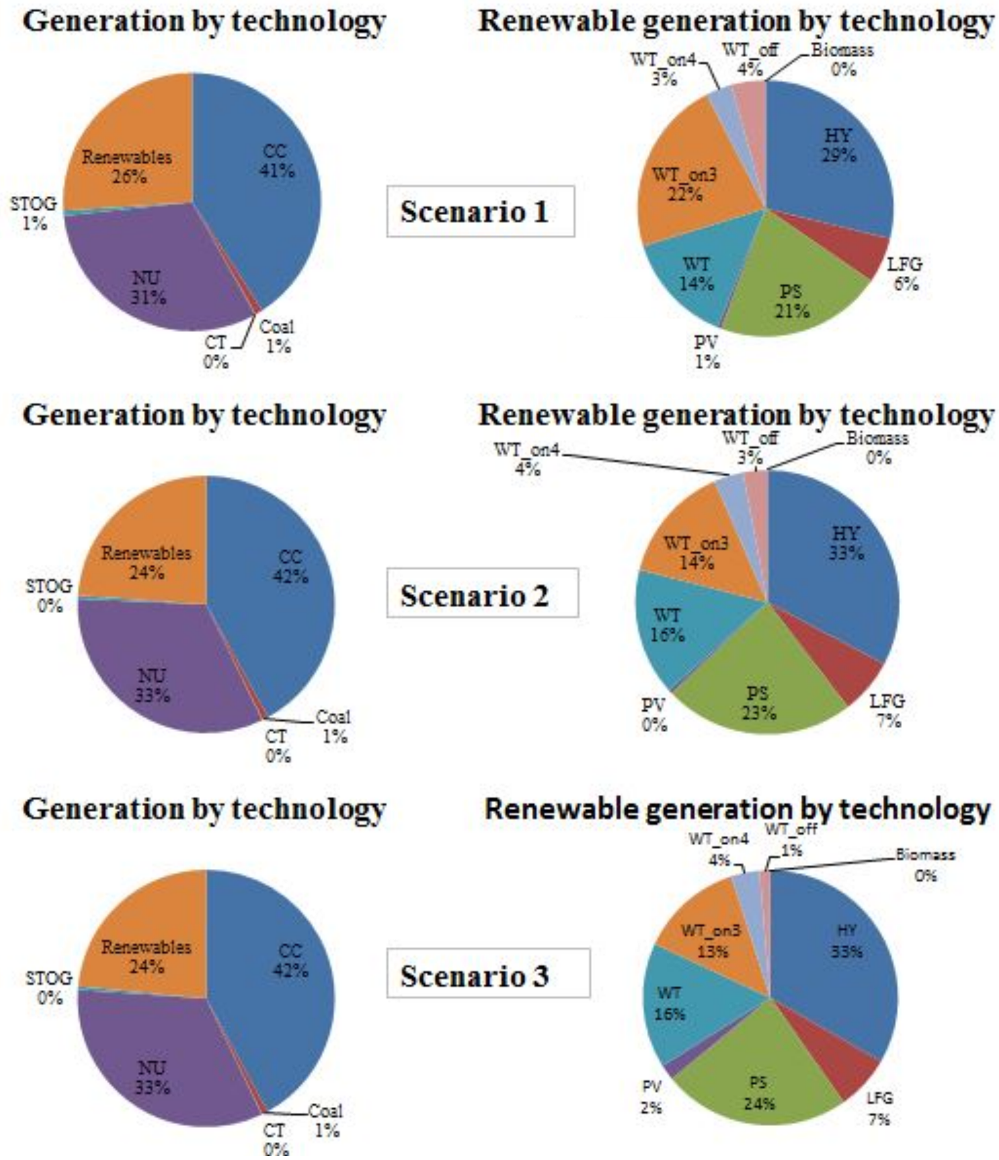

Figure 29 Proportion of total generation by technology in each scenario 2010-2040

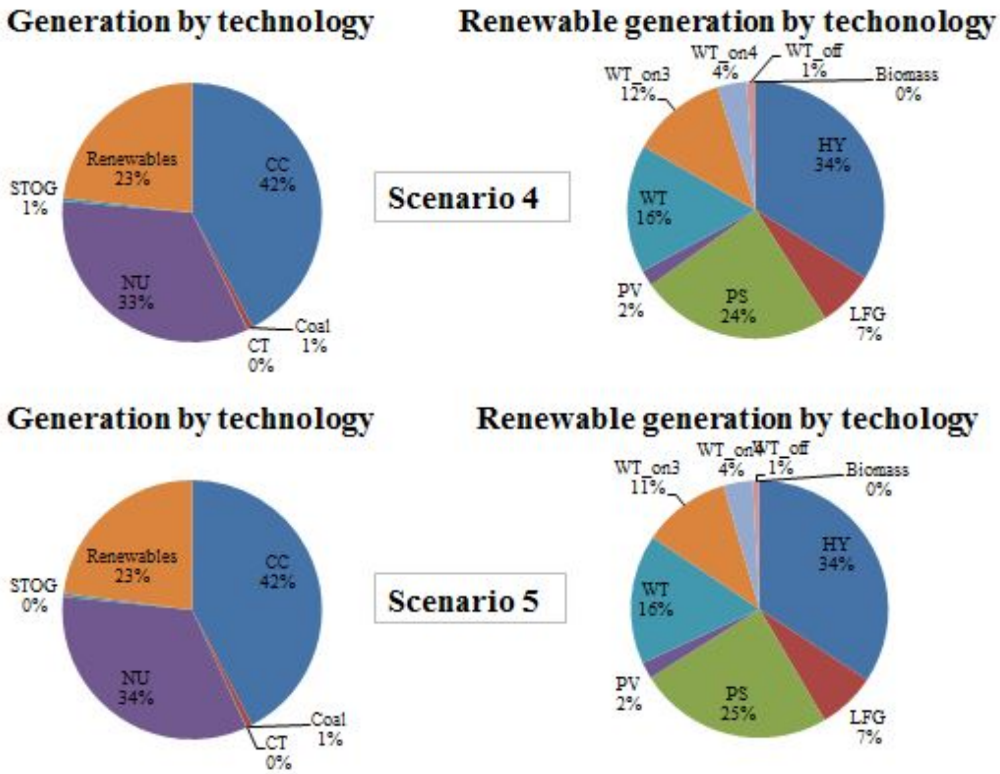

Figure 30 Proportion of total generation by technology in each scenario 2010-2040 (continued)

5.2.4 Energy Prices

We also graph the energy prices in two time periods in a year: summer-peak and shoulder-offpeak, in which the energy prices are the highest and lowest, respectively. They are derived from the shadow prices of energy supply constraints. The high energy price and energy jump around 2010 and 2021 are because of the constructions in 2010-2015 and 2021-2025 as indicated in Figure 31. Energy prices in extreme case Scenario 1 are marginally higher than those in the other scenarios.

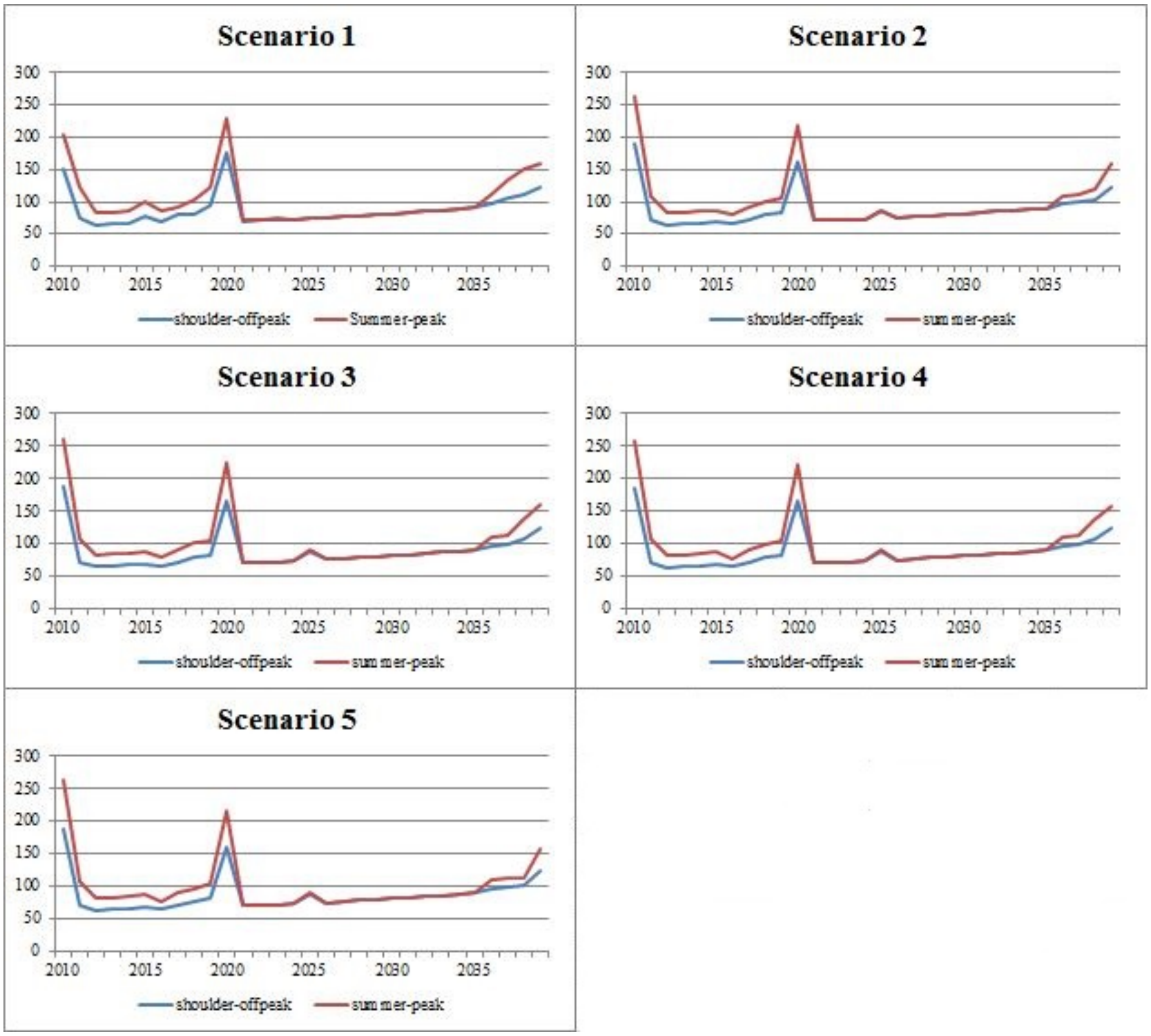

Figure 31 Summer-peak and shoulder-offpeak energy prices in each scenario 2010-2040($/MWh)

5.2.5 Percentage Usages

Once we compare the generation of different types of technologies in Section 5.2.2, it is easy to understand the percentage usage. Percentage usage of a generation unit means the ratio of its actual output to its potential output if it were possible to operate at full nameplate capacity indefinitely over a period of time [77]. It is sometimes also called "capacity factor", but to distinguish it from the GEP parameter, the percentage usage is used in this research. We graph the percentage usage derived from the optimal results in four years, 2010, 2020, 2030, 2040 in Figure 32. We know that combined cycle, conventional hydro, nuclear and pumped storage hydro have percentage usage larger than 50%, some of them even close to 90%. They are the main resources of electricity generation due to low variable costs in all scenarios. Combined cycle are utilized less in the future among all scenarios due to the consideration of emissions, but Scenario 1 has some different patterns than other generation technologies. For instance, nuclear is increasing in Scenario 2-5 while decreasing in Scenario 1.

In reality, conventional hydro and pumped storage hydro are subject to the nature of the river flow or physical conditions, so they cannot actually reach 90% of usage. Particularly for pumped storage hydro, extra electricity is consumed to pump up water. It often serves as a peaker unit, using off-peak extra electricity and produce peak electricity. Our assumptions do not include those conditions due to lack of data, and as a result, conventional hydro and pumped storage hydro become the major resources of power generation.

Figure 32 Percentage usages by technology in each scenario 2010, 2020, 2030, 2040

5.2.6 New Plants Levelized Costs

Levelized cost is often cited as a convenient summary measure of the overall competiveness of different generating technologies. It represents the per-unit megawatt-hour cost (in real dollars) of building and operating a generating plant over an assumed financial life and duty cycle [69]. We try to capture the average cost of a generation unit from construction to operation over a particular period. Therefore, only the levelized costs of new plants, whose investment costs can be included, are studied here.

Normally levelized costs can be calculated by including overnight capital costs, fuel costs, fixed and variable operation and maintenance costs, and assumed percentage usage. Since we have obtained the optimal solution under each scenario, the amount of investments, generation and percentage usage are known. The calculation of levelized cost is straightforward, which can be obtained by dividing the summation of investment costs, generation costs and fixed costs by the summation of generation in the planning horizon.

In Figure 33, most of the levelized costs are between $60-90/MWh in 2010$, and landfill gas has a lower cost around 30 in all scenarios. The extreme Scenario 1 has higher levelized costs for nuclear and class 3 onshore wind turbine. This indicates that those additional costs sum to the energy prices in the extreme scenario. In other words, we are paying more for investment of nuclear and class 3 onshore wind plants in an extreme scenario.

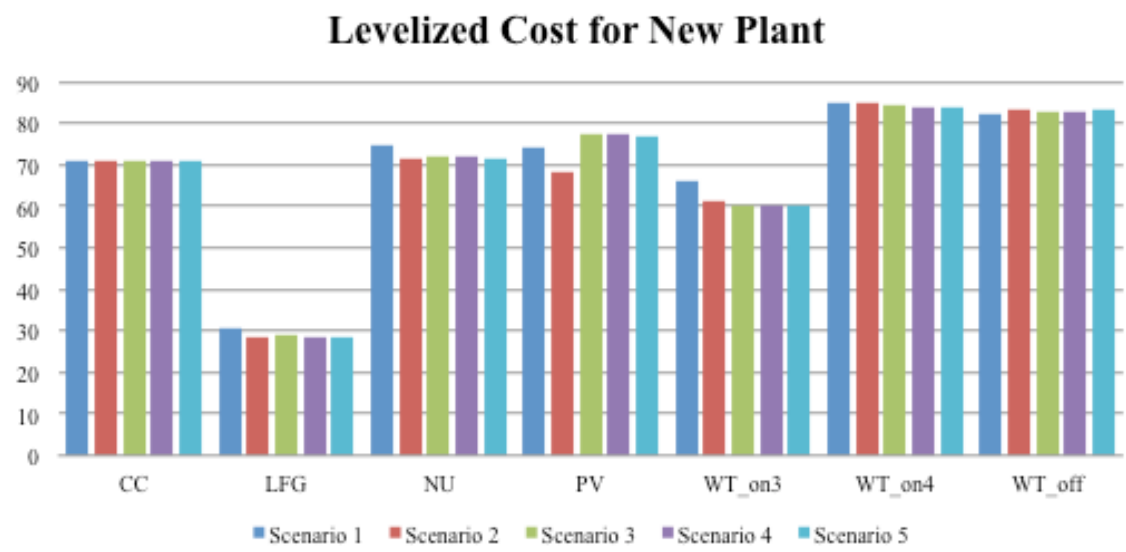

Figure 33 Levelized costs for new technology in each scenario 2010-2040 ($/MWh)

We can compare our results with EIA, e.g., EIA has assumed an 87% usage of combine cycle, then the levelized cost of combined cycle is $67.1/MWh in 2011 dollars, while in our study, combined cycle are working around 60% of time, and the corresponding levelized cost is around 70 in 2010 dollars in all scenarios. Other examples are shown in Table 24. Differences do exist in many ways, so we should also notice that our modeling could be rather different from EIA. It is noted that the levelized costs are quantified differently in 2010 and 2011 dollars.

Table 24 Levelized cost comparison

	EIA (2011$/MWh) [69]	This study (2010$/MWh)
CC	87%, 67.1$	60%, 70$
NU	90%, 108.4$	92%, 70$
PV	25%, 144.3$	30%, 71$
WT_off	37%, 221.5$	40%, 82$

5.3 Conclusion of Scenarios

The scenarios described in our study are realization of three climate variables: temperature, precipitation and extreme events in the planning horizon. Meanwhile, the correlations between climate variables and GEP parameters imply that these scenarios are also realization of six sets of GEP parameters: demands, peak demands, reserve margin requirements, transmission capacity, maintenance time and capacity factors.

Normally the definition of scenarios is largely dependent on the objectives of the GEP models. Here we define an extreme scenario, a base scenario and scenarios built by experts' advices. By solving the GEP models under the constraints subjected to each scenario, we can identify the climate change impacts on the electric power generation expansion planning decisions. Therefore, a detailed analysis is presented in this section by comparing several indices of scenarios.

The results show that the extreme scenario can be significantly distinguished from other scenarios, but all scenarios share a lot of similarities in the choice of generation technologies. The extreme scenario requires much more renewable resources, which leads to higher energy prices. The differences are relatively small for Scenarios 2-5.

6 Robust models

Unlike stochastic optimization, robust optimization is widely adopted for modeling with parameter uncertainty, where deterministic or set-based uncertainty is assumed known. In this research, we assume that climate change remains uncertain but one of the climate scenarios will occur, with the set of uncertain parameters are associated with each scenario. Which scenario will occur is unknown at the decision time, and therefore, a robust decision should be made in advance, that should be effective for any realization of the uncertainty in the given set of scenarios. The robust solution is a compromise optimal solution, neither spending too much for reliability consideration, nor paying too much penalty once underestimating the reality.

As climate scenarios are taken into consideration, slightly different parameters are defined in this section, compared to the preliminary model. It is noted that certain constraints may be violated because of uncertain parameters. Thus we introduce new decision variables: unmet demands and reserve margin requirements, unavailable generation and transmission amount. The unavailable generation and transmission amount is counted into the final unmet demands. Thus only two kinds of penalty costs are considered in the study, costs for unmet demands and costs for unmet reserve margin requirements.

Two robust optimization models are then presented in this section: Model 1 is expected total cost minimization and Model 2 is maximum “regret” minimization. They have nearly the same sets of constraints but different objective functions. In both models, global robust constraints are used for all scenarios by incorporating penalty costs of each scenario. Both models are linear programming models, aiming at finding a good compromise solution under different objectives.

6.1 Nomenclature

The decision variables, indices and parameters of the robust models are described in this section.

Decision Variables

$x_{y,t,r_1,i}$	Generation amount of generation type *i* in region r_1 in time period *t* in year *y* (MWh)
$s_{y,r_1,i}$	Investment amount of generation type *i* in region r_1 in year *y* (MW)
f_{y,t,r_1,r_2}	Transmission flow from region r_1 to r_2 in time period *t* in year *y* (MWh)
$UD_{y,t,r_1,j}$	Unmet demand in region r_1 in time period *t* in year *y* in scenario *j* (MWh)
$UG_{y,t,r_1,i,j}$	Unavailable amount of generation type *i* in region r_1 in time period *t* in year *y* in scenario *j* (MWh)
$UR_{y,r_1,j}$	Unmet reserve margin capacity requirement in region r_1 in year *y* in scenario *j* (MW)
$UT_{y,t,r_1,r_2,j}$	Unavailable transmission amount from region r_1 to r_2 in time period *t* in year *y* in scenario *j* (MWh)
Maxregret	Maximum regret

Indices

j	Scenarios
y	Years, alias *u*
t	Time periods in a year
r_1	Regions, alias r_2
i	Generation types
n	Renewable generation types (subset of *i*)
e	Emission gases

Parameters

r	Interest rate
J	Number of scenarios
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 gases (CO_2, SO_2, $NO_{x...}$)
$c_{y,i}$	Generation variable cost for generation type i in year y (2010$/MWh)
$a_{y,i}$	Investment cost for generation type i in year y (2010$/MW)
p_j	Probability of scenario j
$init_{r_1,i}$	Initial capacity of generation type i in region r_1 at the beginning (MW)
$fnew_{y,r_1,i}$	Forced new capacity of generation type i in region r_1 with online year y (MW)
$fretire_{y,r_1,i}$	Forced retirement capacity of generation type i in region r_1 with retirement year y (MW)
$g_{y,i}$	Fixed operation and maintenance cost for existing generation type i in year y (2010$/MW)
$h_{y,i}$	Fixed operation and maintenance cost for new generation type i in year y (2010$/MW)
$\varphi_{y,t,r_1,j}$	Demand in region r_1 in time period t in year y in scenario j (MWh)
$d_{y,t,i,j}$	Derate rate of generation type i in time period t in year y in scenario j
$hours_t$	Hours in time period t
$cf_{y,t,r_1,i,j}$	Capacity factor for generation type i in region r_1 in time period t in year y in scenario j
$peak_{y,r_1,j}$	Peak load (demand) in year y in region r_1 in scenario j (MWh)
$m_{y,r_1,j}$	Reserve margin for region r_1 in year y in scenario j
$MIN_{y,r_1,n}$	Minimum generation percentage requirement of renewable type n for region r_1 in year y
$TMIN_{y,r_1}$	Yearly minimum renewable generation percentage requirement for region r_1 in year y
$EM_{e,i}$	Amount of emission gas e from generation type i (lbs/MWh)
$RLEM_{e,y,r_1}$	Regional limit for emission gas e in region r_1 in year y (lbs)

$TL_{y,r_1,r_2,j}$ Transmission limit from region r_1 to r_2 in year y in scenario j (MW)

$CL_{y,r_1,i}$ Yearly construction limit of generation type i in region r_1 in year y (MW)

VD_y Penalty cost of unmet demand in year y (\$/MWh)

VR_y Penalty cost of unmet reserve margin requirement in year y (\$/MW)

$Optimal_j$ Expansion cost of optimal solution under scenario j (\$)

6.2 Expected Total Cost Minimization Model

The objective function (11) of the expected total cost minimization model is to minimize the expected total present costs including the penalty costs. The total costs include four parts: investment costs of the new construction, electricity generation costs, operation and maintenance costs, and penalty costs. The first three parts that represent the total expansion costs of the compromise optimal solution are the same as the preliminary model. The fourth part is the expected total penalty costs.

$$\begin{aligned} \min Expected\,COST = \sum_{y=1}^{Y}\Bigg((1+r)^{-y+1}\Bigg(&\sum_{t=1}^{T}\sum_{r_1=1}^{R}\sum_{i=1}^{I} x_{y,t,r_1,i}c_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I} s_{y,r_1,i}a_{y,i} \\ &+\sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(\sum_{u=1}^{y}\left(s_{u,r_1,i}+fnew_{u,r_1,i}\right)\right)h_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(init_{r_1,i}-\sum_{u=1}^{y} fretire_{u,r_1,i}\right)g_{y,i} \\ &+\sum_{j=1}^{J} p_j\left(\sum_{t=1}^{T}\sum_{r_1=1}^{R} UD_{y,t,r_1,j}VD_y + \sum_{r_1=1}^{R} UR_{y,r_1,j}VR_y\right)\Bigg)\Bigg) \end{aligned} \qquad (11)$$

6.3 Maximum Regret Minimization Model

The objective function (12) of maximum regret minimization model is to minimize the maximum regret over all scenarios. Here in our study, regret is interpreted as the difference between desired cost in one particular scenario and the realistic cost under uncertainty in this study. If one particular scenario certain to happen, the deterministic model presented in Section 3 can be solved to obtain the optimal solution under that scenario. However, by the time a decision has to be made, uncertainty lies in the realization of any climate scenario. After the compromise solution is determined at the beginning, one of the future scenarios will actually occur, and the penalty costs can be observed. If we compare the difference between the realistic cost and deterministic optimal cost, the regret can be obtained by subtraction.

Any realization of scenario would lead to a different regret. Here we present a robust optimization model: a minmax problem, which finds the maximum regret over all scenarios and minimizes it. In this case, no probabilistic assumption is associated. We have to determine the “worst case.” From the perspective of regret, the maximum regret case does not necessarily imply extreme scenario. The regret is largely dependent on the initial decision, for example, if the optimal solution of the extreme scenario is chosen to be the compromise solution, then there would be no regret once the extreme scenario happens, but large regret for other scenarios.

$$\begin{aligned}\min\max_j REGRET = \sum_{y=1}^{Y}\Bigg((1+r)^{-y+1}\Bigg(&\sum_{t=1}^{T}\sum_{r_1=1}^{R}\sum_{i=1}^{I} x_{y,t,r_1,i}c_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I} s_{y,r_1,i}a_{y,i} \\ &+\sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(\sum_{u=1}^{y}\left(s_{u,r_1,i} + fnew_{u,r_1,i}\right)\right)h_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I}\left(init_{r_1,i} - \sum_{u=1}^{y} fretire_{u,r_1,i}\right)g_{y,i} \quad (12) \\ &+\sum_{t=1}^{T}\sum_{r_1=1}^{R} UD_{y,t,r_1,j}VD_y + \sum_{r_1=1}^{R} UR_{y,r_1,j}VR_y \Bigg)\Bigg) - Optimal_j\end{aligned}$$

Reformulation

A simple linear programming reformulation is performed for the ease of computation. The original minmax problem has been transformed to a minimization programming by introducing a new decision variable *Maxregret* and adding a group of constraints (14) corresponding to j scenarios. Other constraints remain the same.

$$\min Maxregret \tag{13}$$

s.t.

$$\begin{aligned} Maxregret \geq \sum_{y=1}^{Y} \Bigg((1+r)^{-y+1} \Bigg(& \sum_{t=1}^{T}\sum_{r_1=1}^{R}\sum_{i=1}^{I} x_{y,t,r_1,i} c_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I} s_{y,r_1,i} a_{y,i} \\ & + \sum_{r_1=1}^{R}\sum_{i=1}^{I} \left(\sum_{u=1}^{y} \left(s_{u,r_1,i} + fnew_{u,r_1,i} \right) \right) h_{y,i} + \sum_{r_1=1}^{R}\sum_{i=1}^{I} \left(init_{r_1,i} - \sum_{u=1}^{y} fretire_{u,r_1,i} \right) g_{y,i} \\ & + \sum_{t=1}^{T}\sum_{r_1=1}^{R} UD_{y,t,r_1,j} VD_y + \sum_{r_1=1}^{R} UR_{y,r_1,j} VR_y \Bigg) \Bigg) - Optimal_j \qquad \forall j \end{aligned} \tag{14}$$

6.4 Constraints

The two robust models share most of the constraints (15-23). The only difference is (14) after reformulation depicted in the previous section. Compared to the preliminary model, robust models have more decision variables and parameters associated with each scenario. Constraints (15-17) and (22) differ from (2-4) and (9) due to the uncertainty of scenarios.

$$\begin{aligned} & \sum_{i=1}^{I} \left(x_{y,t,r_1,i} - UG_{y,t,r_1,i,j} \right) - \sum_{r_2=1}^{R} \left(f_{y,t,r_1,r_2} - UT_{y,t,r_1,r_2,j} \right) \\ & \quad + \sum_{r_2=1}^{R} \left(f_{y,t,r_2,r_1} - UT_{y,t,r_2,r_1,j} \right) + UD_{y,t,r_1,j} = \varphi_{y,t,r_1,j} \qquad \forall y,t,r_1,j \end{aligned} \tag{15}$$

$$\begin{aligned} x_{y,t,r_1,i} \leq & \left(init_{r_1,i} + \sum_{u=1}^{y} \left(s_{u,r_1,i} + fnew_{u,r_1,i} - fretire_{u,r_1,i} \right) \right) cf_{y,t,r_1,i,j} d_{y,t,i,j} hours_t \\ & + UG_{y,t,r_1,i,j} \qquad \forall y,t,r_1,i,j \end{aligned} \tag{16}$$

$$\sum_{i=1}^{I} init_{r_1,i} + \sum_{u=1}^{y}\sum_{i=1}^{I} \left(s_{u,r_1,i} + fnew_{u,r_1,i} - fretire_{u,r_1,i} \right) + UR_{y,r_1,j} \geq peak_{y,r_1,j} m_{y,r_1,j} \qquad \forall y,r_1,j \tag{17}$$

$$\sum_{t=1}^{T}\sum_{n=1}^{N} x_{y,t,r_1,n} \geq TMIN_{y,r_1} \sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} \qquad \forall y, r_1 \tag{18}$$

$$\sum_{t=1}^{T} x_{y,t,r_1,n} \geq MIN_{y,r_1,n} \sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} \qquad \forall y, r_1, n \tag{19}$$

$$\sum_{t=1}^{T}\sum_{i=1}^{I} x_{y,t,r_1,i} EM_{e,i} \leq RLEM_{e,y,r_1} \qquad \forall e, y, r_1 \tag{20}$$

$$s_{y,r_1,i} \leq CL_{y,r_1,i} \qquad \forall y, r_1, i \tag{21}$$

$$f_{y,t,r_1,r_2} \leq TL_{y,r_1,r_2,j} hours_t + UT_{y,t,r_1,r_2,j} \qquad \forall y, t, r_1, r_2, j \tag{22}$$

$$\begin{aligned} & x_{y,t,r_1,i} \geq 0, s_{y,r_1,i} \geq 0, f_{y,t,r_1,r_2} \geq 0, UD_{y,t,r_1,j} \geq 0, \\ & UG_{y,t,r_1,i,j} \geq 0, UR_{y,r_1,j} \geq 0, UT_{y,t,r_1,r_2,j} \geq 0, \qquad \forall y, t, r_1, r_2, i, j \end{aligned} \tag{23}$$

Compared to (2), equations (15) allow unmet demands if the generation and the transmission electricity amount of the compromise solution cannot meet the demands in some scenarios. Constraints (16) are capacity constraints, which allow unavailable capacity if generation exceed the total capacity in some scenarios. Constraints (17) are reserve margin requirements constraints that allow unmet capacity. Constraints (18-21) remain the same as (5-8). Constraints (22) represent transmission capacity limits that allowing unavailable transmission in some scenarios, (23) are nonnegative constraints.

7 Numerical Examples

Considering the two robust models in previous section, how to evaluate those models and how to choose between those two options are our concern. Therefore, numerical examples are tested and compared in this section.

7.1 Assumptions

While most of the assumptions keep consistency with the preliminary model, we need clarification of new assumptions. The cost of unmet demand is normally called Value of Lost Load (VoLL) with typically range of $1,000-20,000/MWh [57]. Here we assume the unmet demand cost to be $2000/MWh (in 2010 dollars) with a growth rate of 2% as a reasonable value, while the cost of unmet reserve margin requirements is assumed to be 1.5 times the investment cost of combustion turbine. Since combustion turbine has the lowest investment cost, in order to meet the reliability requirements, it is desired to invest in the most economic technology. Scenarios 1 through 5 have probabilities of 0.1, 0.3, 0.3, 0.2, 0.1. We assume that Scenario 1 is the extreme case with 0.1 probability, and climate change is likely to occur, and thus Scenario 5 is also less probable to happen. Scenarios 2 and 3 origin from the projections of experts, and we assign them larger probabilities. The assumed probabilities are only used for numerical purpose. Again GAMS/CPLEX is used to solve the robust optimization models.

7.2 Results Comparison

When we scrutinize the total expansion costs in Figure 34 (note that in order to compare with each scenario, expansion total costs do not include the penalty costs, but penalty costs are considered in the optimal objective function values), total investments in Figure 35 and total generation in Figure 36, we can easily understand that our robust solutions are more like compromise solutions. In Figures 35 and 36, instead of using Scenarios 2-5 individually, we average them since results of Section 5.2 show that Scenarios 2-5 are similar. However, we emphasize the extreme case Scenario 1.

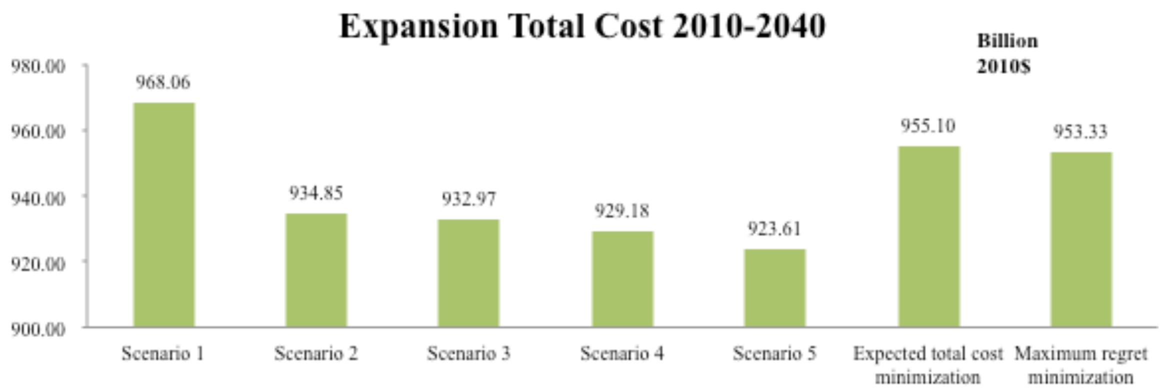

Figure 34 Expansion total costs for different models 2010-2040 (Billion 2010$)

Figure 35 illustrates the compromise solutions, which do not invest too much to pay for the extreme case, but do reserve more capacity in case of extreme weather. Unlike discrete scenario solutions, compromise solutions in both models invest in AC and IGCC instead of PV and WT_off. It may imply that advanced fossil technologies are alternative choices for planning under uncertainty. Generation has some similarities with investments in the compromise solutions. GEO, AC and IGCC take part in the generation to combat uncertainty (Figure 36).

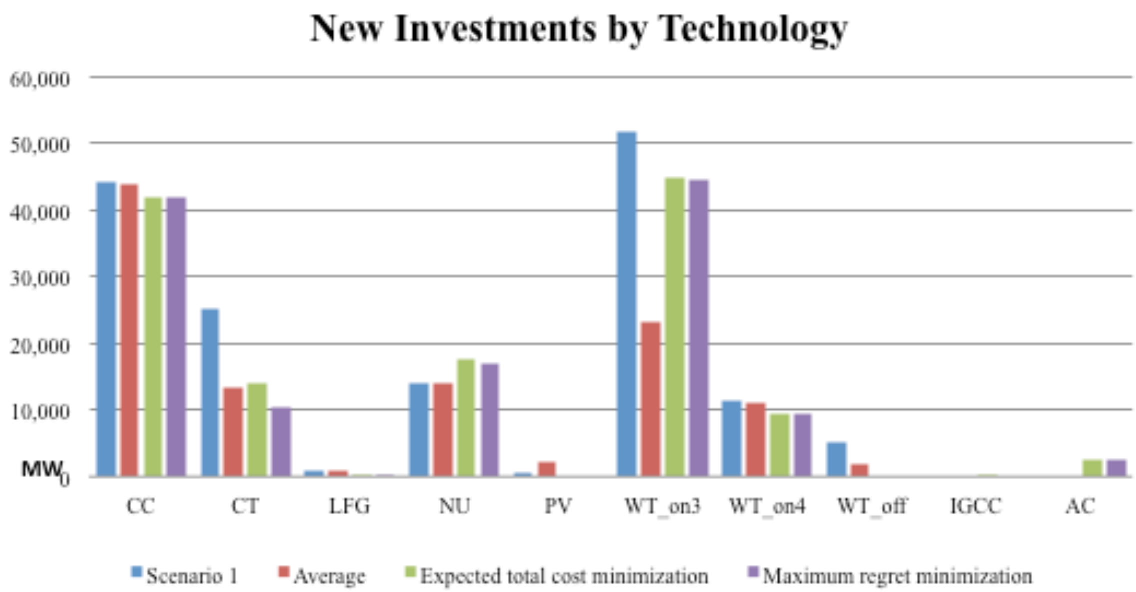

Figure 35 Total investments for different models 2010-2040 (MW)

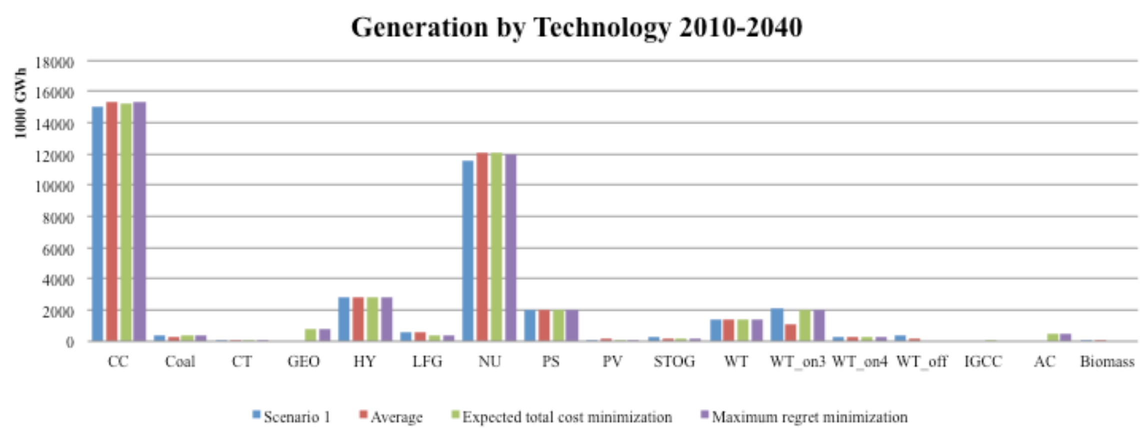

Figure 36 Total generation for different models 2010-2040 (1000GWh)

It is interesting to compare the expected total cost minimization model and maximum regret minimization model. In this example, expected total cost minimization model gives a more satisfactory solution as shown by the blue bar in Figure 37, especially when their expansion total costs are quite close. The expected total cost minimization model only has penalty in Scenarios 1 and 5, while the other model has more penalty costs in nearly every scenario. Although the expected total cost minimization model has slightly higher regret in Scenario 5, on average, it has less regret.

On the other hand, maximum regret minimization model (red bar) does provide a solution with least maximum regret around 29.7 Billion in 2010 dollars, but it is not a significant improvement compared to the 31.7 Billion in 2010 dollars of the expected total cost minimization model. Meanwhile, the maximum regret minimization model gives us an equal regret under each scenario, which means, no matter how the future climate would be, we will have a certain regret. This indeed diminishes the uncertainty or variance; however, policy makers will not favor it as the average penalty cost and regret are both too much.

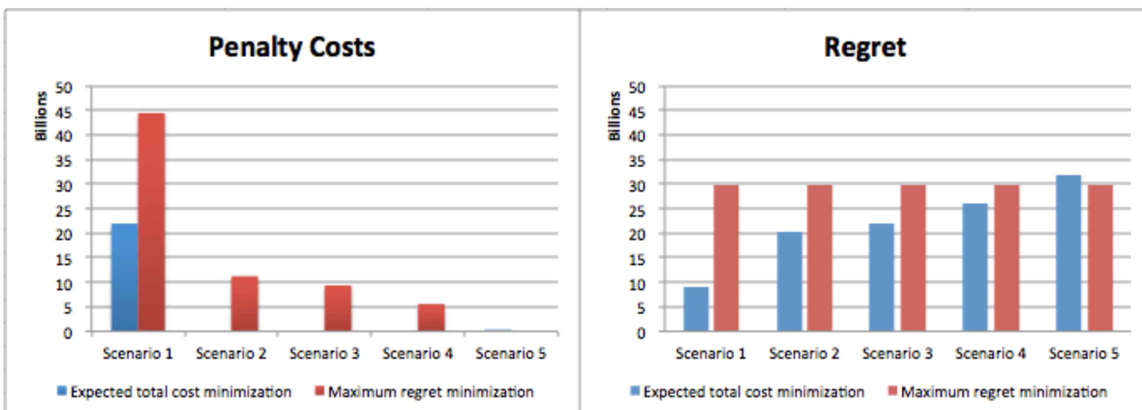

Figure 37 Penalty and regret comparison (Billion 2010$)

7.3 Sensitivity Analysis

A lot of questions follow the results in Section 7.2:

- Is expected total cost minimization model always good?
- How will the model results change once the probabilities change?

- Will maximum regret minimization model always give results of equal regret for each scenario?
- How will the model results change once the unit penalty cost change?

Therefore, a sensitivity analysis is conducted to inspect whether it is just a special case or it can be generalized to some extent. We only examine the probability and unit penalty cost sensitivities on a simple basis in this research.

In previous discussion, the probabilities assigned to Scenarios 1-5 are 0.1, 0.3, 0.3, 0.2, 0.1, which implies that the extreme scenario has 10% of chance to happen. We design another sets of probabilities, in which the future climate is less extreme. The probability of Scenario 1 decreases to 0.02, while probabilities of other Scenarios increase equally. Then the new sets of probabilities are 0.02, 0.32, 0.32, 0.22, 0.12 for Scenarios 1-5.

Another design is to increase the unit penalty cost for unmet demand. We observe cases that once the unit penalty cost is too low, it is desired to pay the penalty costs rather than invest new plants or generate more electricity. We raise the unit penalty cost of 2010 from 2000$/MWh to 5000$/MWh, still in the range of 1,000-20,000$/MWh, keeping the yearly growth rate of 2%. Unit penalty cost for unmet reserve margin requirements is not changed.

The sensitivity analysis design is listed in Table 25, in which we label every combination of conditions as A-F. After solving the six cases individually, we present pairwise comparisons to identify particular features: A vs B vs C, D vs E vs F, A vs D, B vs E, C vs F.

Table 25 Sensitivity analysis design

	Expected toal cost minimization		Maximum regret minimization
	More extreme (p_1=0.1)	Less extreme (p_1=0.02)	
Low unit penalty cost (2000$/MWh)	A	B	C
High unit penalty cost (5000$/MWh)	D	E	F

7.3.1 A vs B vs C

Under a low unit penalty cost assumption, B has a much lower expansion cost (Figure 38) as we assume the extreme scenario is very unlikely to occur. Therefore, solution B is an optimistic decision. However, once Scenario 1 happens as shown in Figure 39, there are extreme penalty and regret associated with Scenario 1. It is noted that A and C are precisely what were discussed in Section 7.2.

Another important message conveyed by Figure 39 is that although solution B has a very large penalty and regret in Scenario 1, for Scenarios 2-5, solution B gives negative regrets. It is strange as it seems to cost less than the optimal solution for each scenario. The reason is that the preliminary model does not allow any unmet demand, unavailable capacity or unmet reserve margin requirements, while the robust model allows that with the limitation that penalty costs should be included. Consequently, compromise solution B chooses to pay a penalty instead of investment or generation.

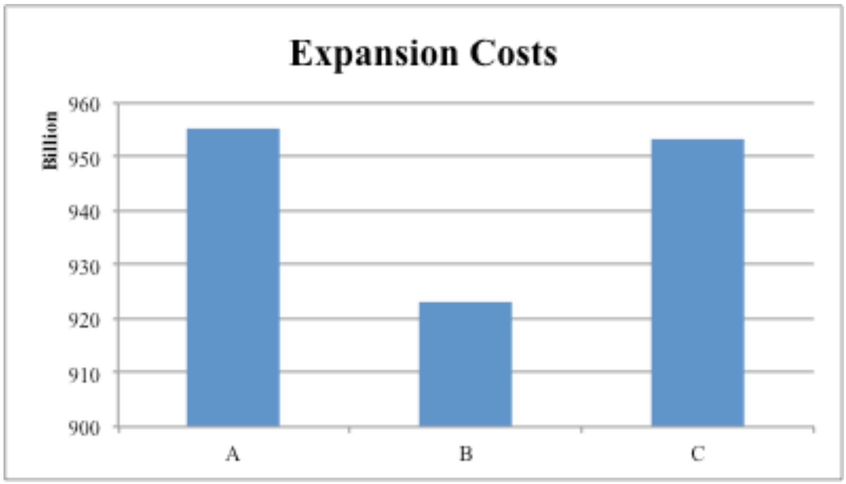

Figure 38 Expansion costs under low unit penalty cost for A, B and C 2010-2040 (Billion 2010$)

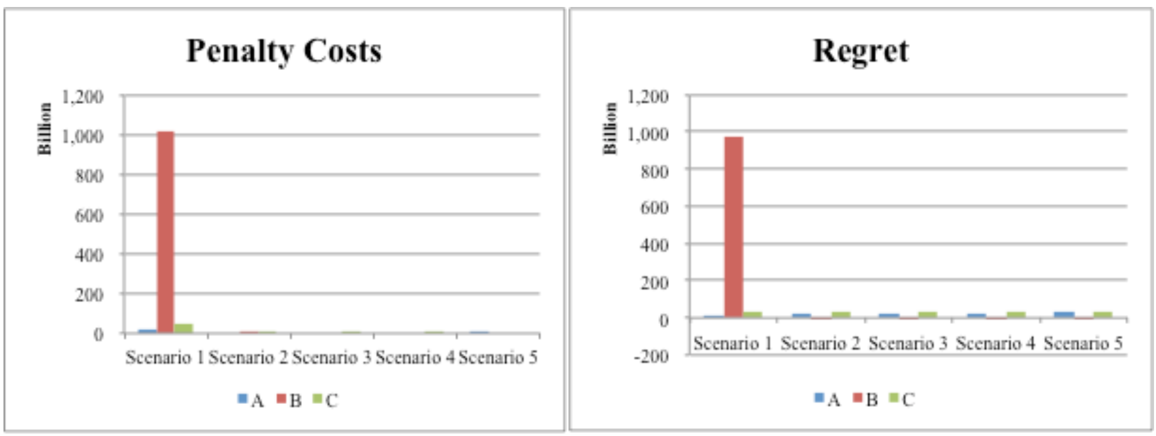

Figure 39 Penalty and regret under low unit penalty cost for A, B and C 2010-2040 (Billion 2010$)

7.3.2 D vs E vs F

We raise the unit penalty cost and run the same models again. The results show that probabilities are not significantly affecting the compromise solutions (Figures 40-41). D and E have almost the same results in expansion, penalty costs and regret. Both D and E lead to large regrets when the extreme scenario occurs. Solution F is much better in this case, it spends four Billion 2010 dollars and gets much lower regrets in return, except that it has penalties for Scenarios 1-4. Compromise solutions D and E only have penalties in Scenario 1, but have regrets in all scenarios.

We may infer from the results of Sections 7.3.1 and 7.3.2 that expected total cost minimization model is desired under a low unit penalty cost case. On the contrary, the maximum regret minimization model performs better under a high unit penalty cost case. However, further studies are necessary for confirmation.

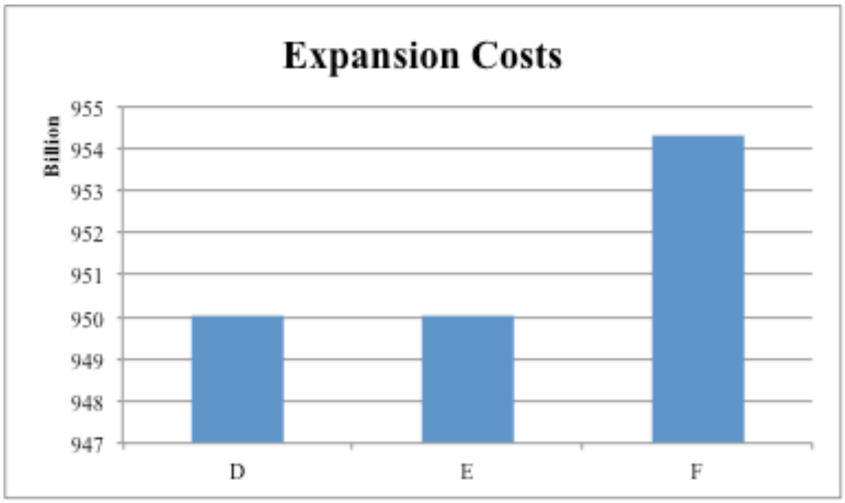

Figure 40 Expansion costs under high unit penalty cost for D, E and F 2010-2040 (Billion 2010$)

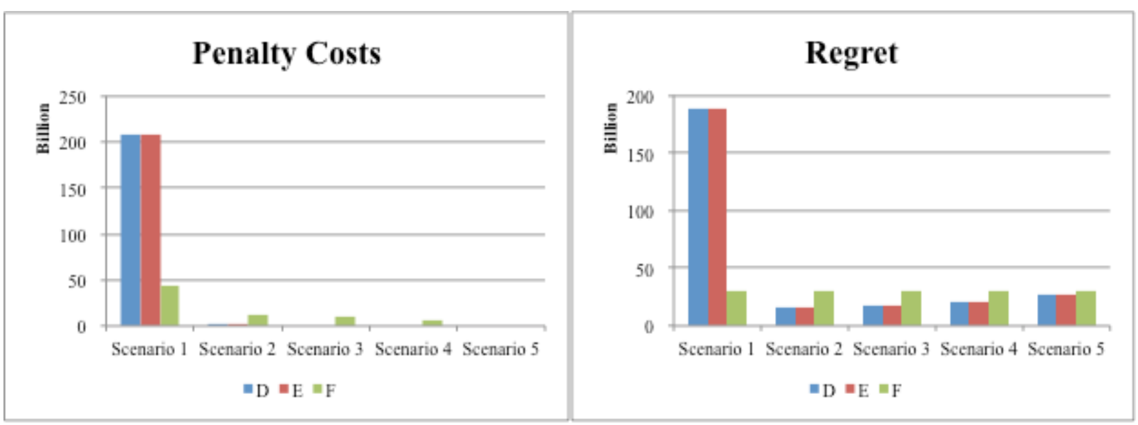

Figure 41 Penalty and regret under high unit penalty cost for D, E and F 2010-2040 (Billion 2010$)

7.3.3 A vs D

A and D are compared in Figure 42, which indicates that the low and high unit penalty cost under a more extreme future cases are solved using the expected total cost minimization model. We assume that Scenario 1 is going to happen at a 0.1 level.

Solution D spends less for expansion, and as a result, it has a much more penalty for extreme scenario. Hence higher unit penalty may lead to lower expected cost, but bring more risk when response to extreme climate.

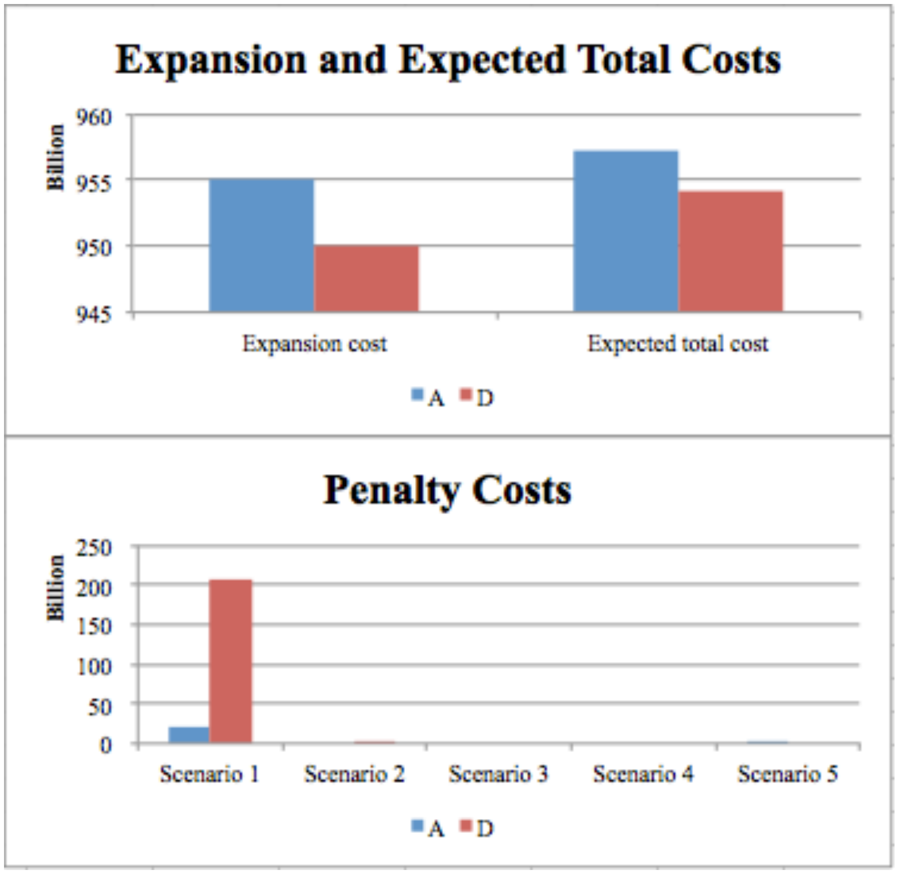

Figure 42 Expansion, expected total and penalty costs under more extreme future for A and D 2010-2040 (Billion 2010$)

7.3.4 B vs E

When we assume a less extreme future, the results are on the opposite direction (Figure 43). Higher unit penalty leads to higher expansion cost but lower penalty.

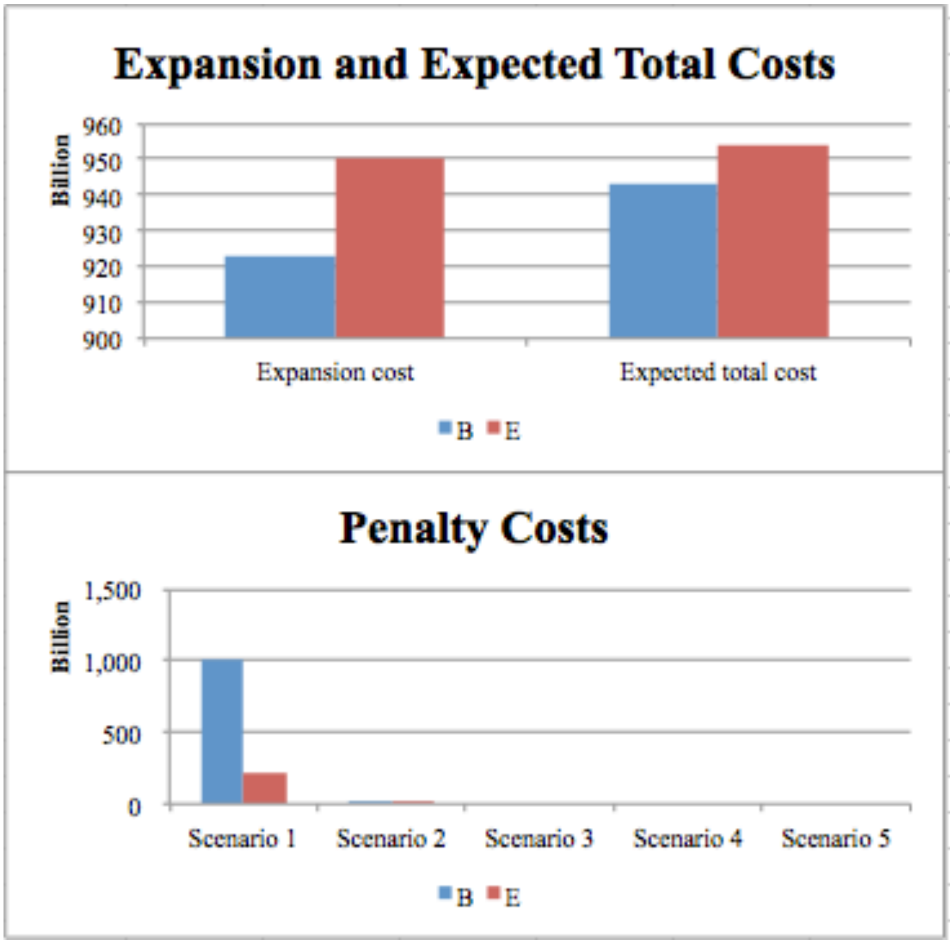

Figure 43 Expansion, expected total and penalty costs under less extreme future for B and E 2010-2040 (Billion 2010$)

7.3.5 C vs F

The maximum regret minimization model has been solved under low and high unit penalty cost assumptions and the results are shown in Figure 44. The penalty costs for scenarios in C and F are literally the same. Thus the differences in the expansion costs are exactly displayed in the regret. It is noted that the same penalty dose not imply the same unmet demand, because of the low and high unit penalty cost assumptions. Under both assumptions, we have equal regret for each scenario. It may lead to the deduction that the maximum regret minimization model reduces variance as much as possible, but a theoretical proof is needed.

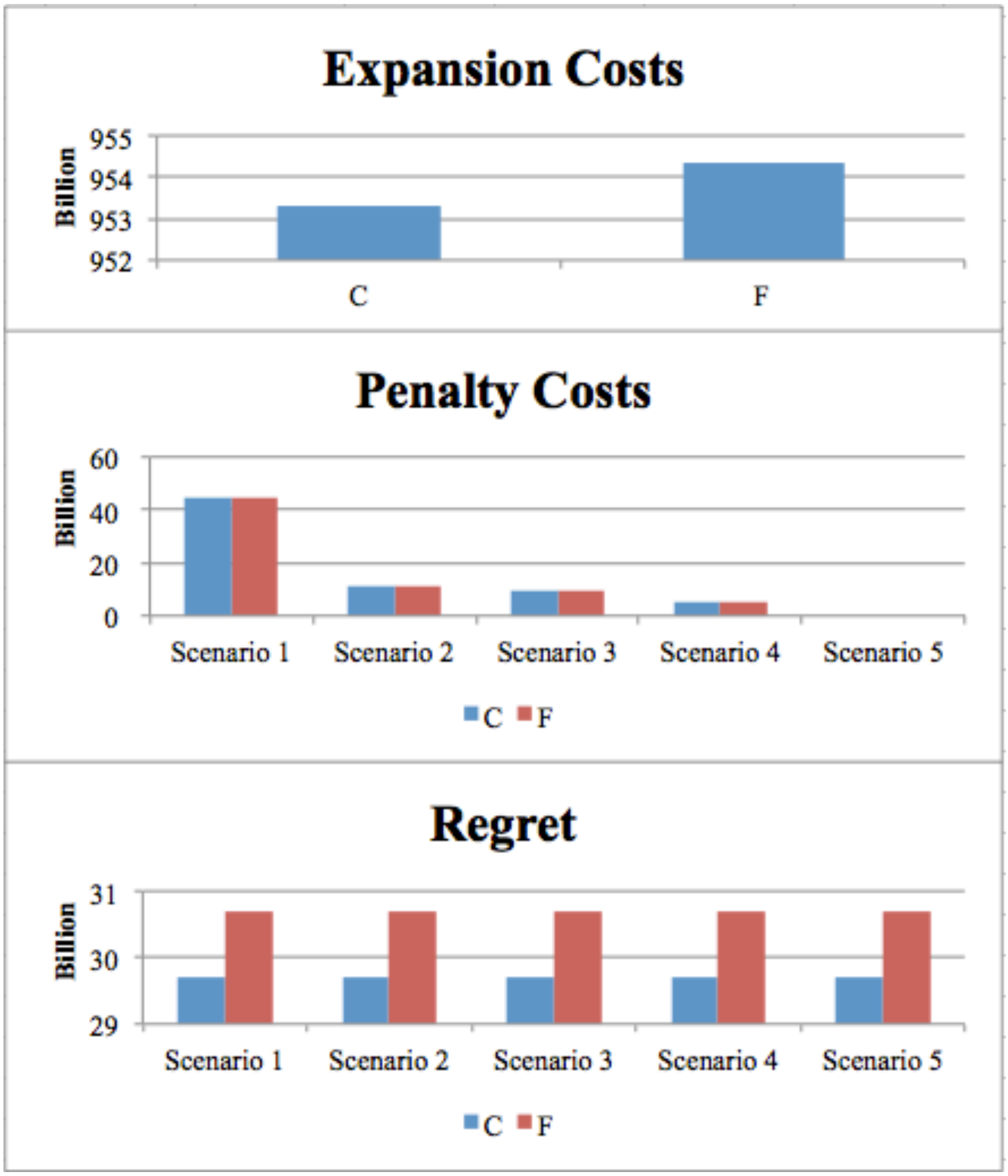

Figure 44 Expansion, penalty costs and regret for C and F 2010-2040 (Billion 2010$)

7.4 Conclusion of Numerical Example

We present two robust optimization models in previous section and the numerical example in Section 7. The models work effectively and can obtain satisfiable solutions.

Both the expected total cost minimization and maximum regret minimization models give us compromise solutions, avoiding investing too much for the extreme case as well as keeping extra reliability for other scenarios. Subjected to global constraints, these two models can solve the GEP problems robustly, with emphasis on different objectives.

In terms of comparison of the two models, their performances vary. We conduct a sensitivity analysis for the comparison of the models by changing parameters. Under a high unit penalty cost case, maximum regret minimization model seems to be a better option, while expected total cost minimization model is desirable when the unit penalty cost is relatively low. If the extreme scenario is less likely to happen, results show that it is better to pay penalty rather than invest. Both the unit penalty cost and the probability of the extreme scenario significantly influence the electric power generation expansion decisions. Different combination of them would lead to different solutions. Meanwhile, the maximum regret minimization model provides equal regret for each scenario, which can reduce the variance to the most extent.

8 Conclusions and Future Directions

In this research, a detailed study of electric power generation expansion planning considering uncertainty of climate change has been carried out. We refer to a large amount of literature to construct a preliminary GEP model, collect data from various resources and validate our model by comparing our results with EIPC. The input of the preliminary model serves as the base scenario in later discussion.

As we take the uncertainty of climate change into consideration, discrete climate scenarios method is adopted. Five climate scenarios are defined based on the quantifiable relationships between climate variables and GEP parameters extracted from the projections of experts. We solve the five scenarios independently and obtain the optimal solution under each scenario, then the climate change impacts can be identified by comparing the results. The extreme scenario is shown to have the largest impacts on the expansion decisions.

We present two formulations of robust optimization, expected total cost minimization and maximum regret minimization models. Both models provide good compromise solutions with different performances under different configurations of GEP parameters. The models are proved to be theoretically valid and work efficiently by conducting sensitivity analysis.

The research is limited by the complexity of the GEP problems and preciseness of climate projections. Appropriate assumptions are made accordingly. But the results provide certain reference for power system modeling under uncertainty and risk management. Future studies can extend the spatial and temporal scale of this research, as well as include more constraints (policies and regulations, economy and demography, climate and geology, etc) and more effective data from advanced research.

The deductions of the results in this study can be further investigated, especially the choices of different technologies and the objective functions of the two robust optimization models. A combination of mathematical proof and practical application is suggested for future research. Further comprehension of power system and climate change requires the coordination of researchers from climate change, power system, mathematics and engineering fields.

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