Strategic Investment in Power Generation under Uncertainty
Electric Reliability Council of Texas

by

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Abstract

The purpose of this study is to develop a strategy for investment in power generation technologies in the future given the uncertainties in climate policy and fuel prices. First, such studies are commonly conducted using deterministic methods which assume a given likelihood of the carbon and gas price levels. In this study a probabilistic approach is used to address these uncertainties. Secondly, capacity expansion models conventionally apply average estimates to predict the amount of power that each generator will produce based on the technology chosen. I propose an alternate method which determines the actual generation hour-by-hour of a generator. Using this method, I also capture the variability of wind generation across the year.

To accomplish this goal, I used the Electric Reliability Council of Texas (ERCOT) as a case study. I investigated the effect of different scenarios of generation technology investments projected over a period of twenty years. I conducted two sets of analyses; first assuming that Carbon Capture and Storage (CCS) technologies will be available after 2020, then assuming that they will not. Using a dispatch model, I simulated the hours of a load duration curve for 2020 and 2030. In the first period 2010-2020, I assumed the price of carbon to either be \$0 or \$50/ton CO_2. In the second period, I take the carbon price to be at either a low of \$25/ton of CO_2 or a high of \$100/ton of CO_2. The price of natural gas used was either a high of \$15/MMBtu or a low of \$3/MMBtu in both periods. Using a Monte Carlo, I sample the wind generation based on the season and the time of day. The system costs with the new investment scenarios were then evaluated in a decision tree to establish the socially optimal solution.

I find that the optimal strategy to be taken today depends on the availability of CCS technologies in 2030. Assuming that there is CCS in 2030, the more dominant strategy would be to build natural gas generators today. If we assume that there is no CCS in 2030, the strategy would depend on the probabilities of the levels of gas and carbon prices in 2020.

Thesis Supervisor: Mort D. Webster, Assistant Professor, Engineering Systems Division

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1.0 INTRODUCTION AND MOTIVATION

The electricity sector produces 40% of carbon emissions from the energy sector from combustion of fossil fuels (EIA, 2009). Currently, no climate policy addresses carbon emissions but when one is established, it will heavily impact the electricity power sector. For now, both the price and the time when a climate policy will be established remain uncertain. In the power sector, a price on carbon will change the cost structure of fossil generation technologies and operation costs will increase as a fraction of the total cost of generation. This is an important consideration in capacity expansion planning. Figure 1.1 characterizes the cost structure of a pulverized coal plant for every KWh produced.

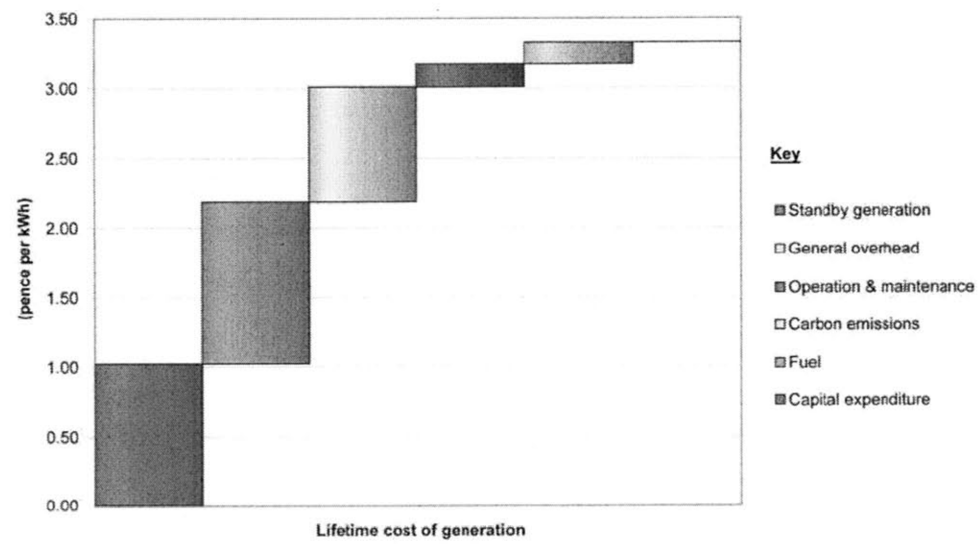

Figure 1.1: Cost Structure of a Pulverized Fuel Coal Generator (Royal Academy of Engineering, 2004)

In Figure 1.1, the price of emissions assumed is $15 or £8.20 in 2006 value. However, the price on carbon is uncertain and can in fact be higher or lower than that shown in Figure 1.1. The rectangle representing carbon emissions can in the future be either bigger or smaller depending on the price that will be set. For fossil fuel technologies the cost of carbon emissions may become a significant fraction of the total cost of generation. Studies have used prices ranging from 10$/ ton of CO_2 to as high as $200/ton of CO_2.

One way to reduce carbon emissions is by switching to less carbon intensive fossil fuels (MIT Study on the Future of Coal, 2007). Natural gas has been identified to produce fewer emissions than both coal and oil. However, an increased demand in natural gas, which can also be used in the transportation sector, may result in high natural gas prices. In the summer of 2008, the US price of natural gas was as high as $8.86/MMBtu from an average of $3.54/MMBtu according to the EIA. Figure 1.2 shows forecasts in the short term showing the upper and lower bounds of the expected prices.

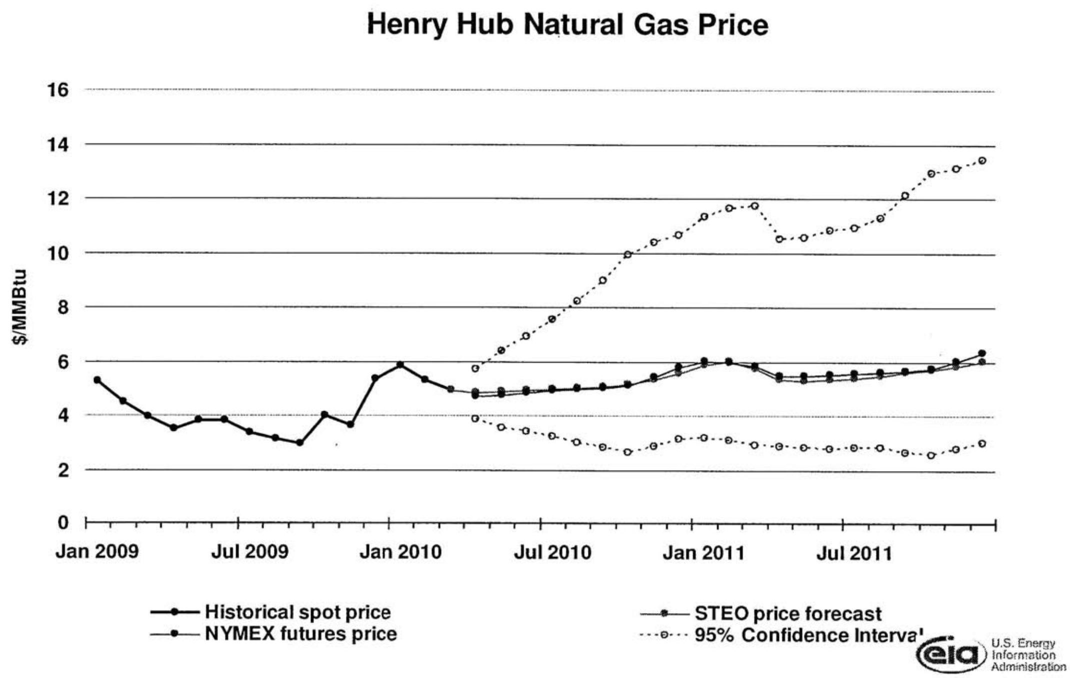

Figure 1.2: EIA Short Term Natural Gas Outlook (EIA, 2010)

In Figure 1.2 we see the price of natural ranging between $13.43 and $2.99 by December 2011. The uncertainty in natural gas price is therefore an important factor for expansion planning.

Another way to reduce dependency on high-carbon fuels is through the use of renewables (MIT Study on the Future of Coal, 2007). Interestingly, these have high capital costs and low availability factors which are also unfavorable to investors. Moreover, they pose numerous reliability complications from the system operator's perspective. Figure 1.3 shows the cost structure of an onshore wind generator.

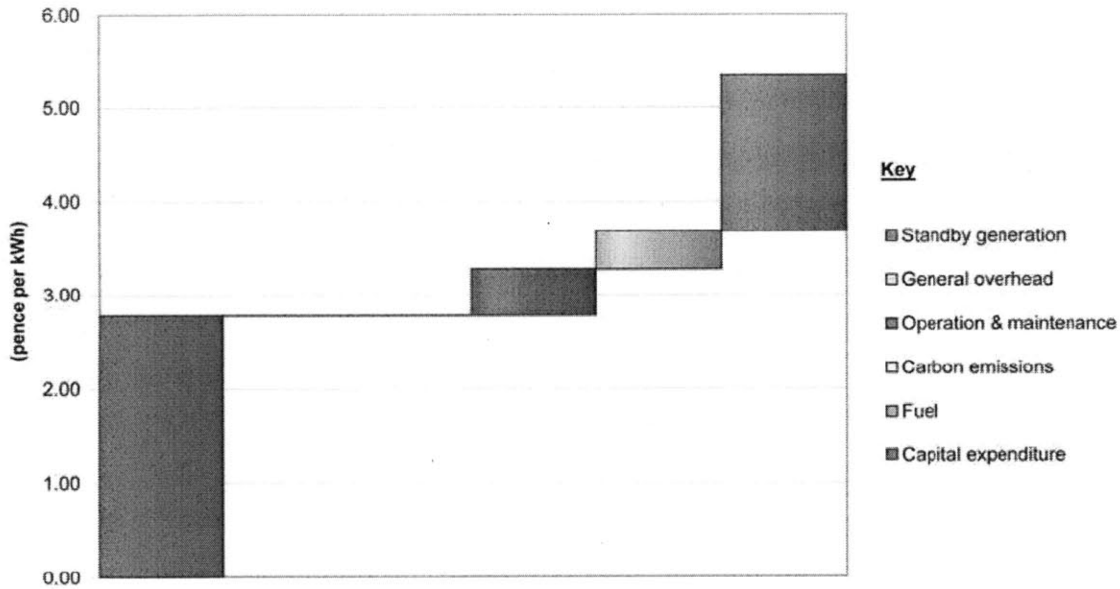

Figure 1.3: Onshore Cost-structure of a wind farm (Royal Academy of Engineering, 2004)

The majority of the costs of generating electricity from wind are capital expenditure as shown in Figure 1.3. The capital cost is almost three times that of building a coal plant. However, operation and maintenance costs are minimal and there are no fuel costs. The standby generation cost is the cost of having readily available generators on standby for reliability concerns (Royal Academy of Engineering, 2004). These costs are a result of the intermittency and variability of wind. While average estimates have been used to calculate the expected revenue generated from wind farms, a better representation of these is necessary so as to be more accurate in predicting wind electricity production.

Other ways to reduce the amount of carbon emissions from the power sector are through increased use of nuclear energy, increasing technology efficiencies, and also carbon capture and sequestration (CCS) (MIT Study on the Future of Coal, 2007). CCS is however still not commercialized and its availability is also uncertain. In this thesis, I do no not include nuclear energy.

The aim of this study is to provide a strategy for power generation capacity expansion despite these looming uncertainties to avoid risk. I investigate the evolution that generation technologies will most likely take as a result of the uncertain carbon price and natural gas. My question is:

"Given the uncertain climate policy and fluctuating natural gas prices, what generation technologies should be invested in today to avoid risk to the investor?"

Traditionally, capacity expansion has been deterministic even in the analysis of uncertainties through the use of scenario analysis. Long term planning usually takes a deterministic characteristic while short term operations use probabilistic decision making. To address this question, I propose a probabilistic approach which compares options under different states of the uncertainty and probability as the method employed by Mort et al, 2008 and Mort et al, 2009 to analyze uncertainty in greenhouse emissions and costs under various scenarios. Though there are numerous uncertainties in expansion planning, such as demand, and demand response, I assume that the uncertain carbon price and natural gas prices are significant drivers in expansion in today's energy climate.

I employ dynamic programming which allows for the problem to be solved or optimized over multiple periods. A multi-stage decision making process allows for flexibility in the design of the capacity expansion plan. A one-time decision would lock in the investors in a potentially risky investment given the changes that may occur throughout the period in question. In addition to the focus on the uncertainties, I propose the use of short term dispatch model to assess the costs of the system. Specifically, I try to capture the hour-by-hour costs of running the system in the future to decide on the technology option today. The main motivation behind this is to illustrate the variability in wind production based on historical seasonal and daily patterns.

The hypothesis is that the method used in this study provides more accurate system costs under each of the states of uncertainty because of the hour-by-hour approach taken. Additionally, using decision analysis is a more useful tool than deterministic approaches. The targeted audiences for this thesis are investors, system operators, and policy makers such as the Public Utility Commissions.

To accomplish these aims, I use the Electric Reliability Council of Texas (ERCOT) as a case study. The generation technology portfolio for Texas, like the rest of the country, has evolved over time as a result of changing market and environmental regulation. Electricity demand continues to grow in Texas at an average annual rate of 2%, and today environmental regulation plays an even more important role in the choice of technologies as efforts to move towards a low-carbon economy increase. Figure 1.4 shows the evolution of each of the main energy sources in Texas from 1990 to 2007.

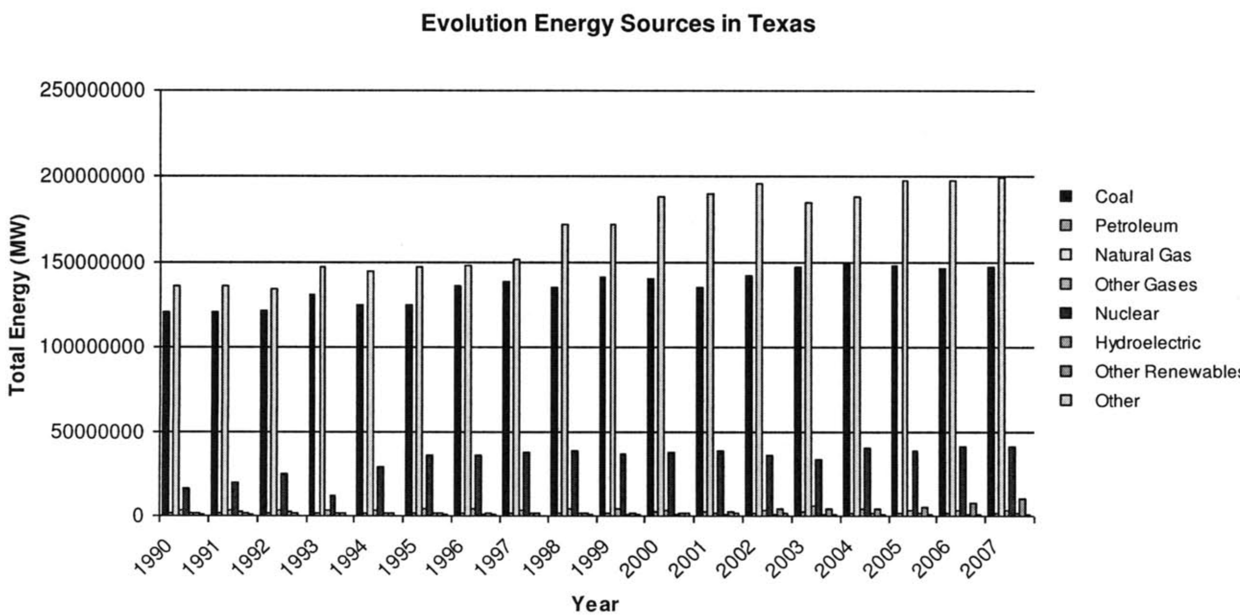

Figure 1.4: Evolution Energy Sources in Texas (data adapted from EIA, 2007 edition)

In Figure 1.4, "Other Gases" include propane gas, and blast furnace gas; "Other Renewables" include wood, solar thermal, geothermal, and wind; and "Other" includes chemicals, and batteries. As seen in Figure 1.1, the investment in natural gas has been increasing rapidly while there has been relatively less growth in coal investment. Seventy-seven new natural gas plants have been connected to the grid in Texas since 1995 (Texas House Committee Select, 2009). The increase in the price of natural gas in recent years, however, suggest that investment in natural gas plants is more risky than other fuels, even coal. There has also been an increase in nuclear generation, though legislative constraints remain an impediment in its adoption in the future. While renewable resources still make up a small percentage of total energy, there has been a significant rise in investment mostly in wind. This is largely a result of both state and federal programs that encourage investment in renewables through incentives for climate change mitigation and increased energy sustainability. A notable example is Texas' Renewable Portfolio Standard (RPS) which was first implemented in 1999, and has so far been one of the most successful in the nation. Under a RPS, electric utilities are required to purchase a portion of their electricity from renewable sources (Wiser, 2002). Finally, hydroelectricity has been declining over the years due to high costs in building the plants. Figure 1.2 shows the current composition of ERCOT generation capacity.

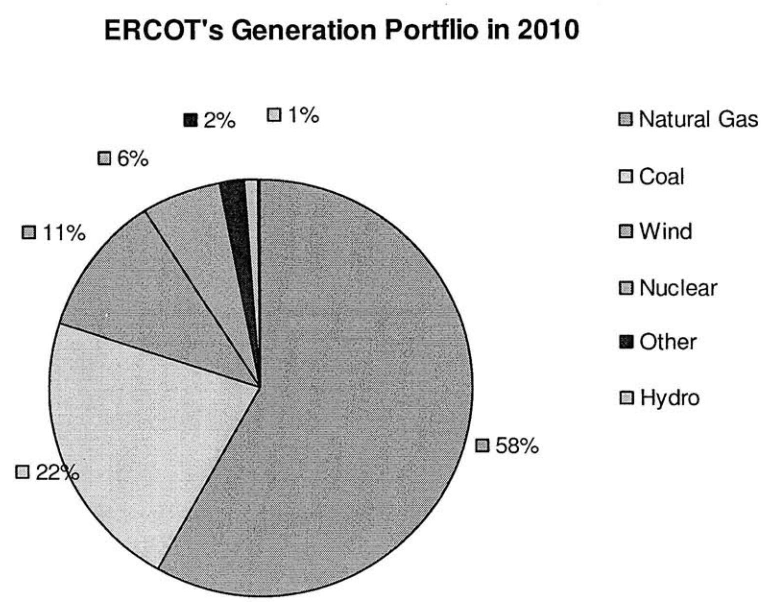

Figure 1.5: ERCOT Generation Portfolio in 2009 (ERCOT, 2010)

Natural gas continues to dominate the region's generation portfolio. Coal generation has slightly increased and wind now makes a signification portion of the region's fleet. These three fuel types are the focus of this thesis.

Using ERCOT as a case study, I develop an investment strategy by determining socially optimal technology portfolio for the next twenty years till 2030 from a number of portfolio scenarios. The optimal solution is simply the system that results in the least total costs including capital and operation. I design the portfolios investigated here using simple screening curves. To solve this as a dynamic programming problem, I assume that there are two decision periods 2020 and 2030. I simulate each hour of each of these years, and I use a dispatch model to evaluate the different scenarios focusing on the uncertainties and the wind production. Using a decision tree, I conduct various analyses to determine the optimal solution which is the system with the lowest total system costs.

This thesis is organized as follows. In Chapter 2, I provide a literature review of other studies that have been done on this topic and discuss the methods which are used in the approach of this study. The methodology used is detailed in Chapter 3. The different scenarios of technology investment are presented here. In Chapter 4, I give the results of the analysis giving the optimal technology choice from the system operator's perspective. In Chapter 5, I discuss these results and provide insight for policy consideration and give policy recommendations.

2.0 LITERATURE REVIEW

Capacity expansion has employed numerous approaches; individual methods and syntheses of two or more methods. Most commonly used are deterministic models which optimize a given set of parameters to give the optimal solution. Decisions made from deterministic models ignore uncertainties that that are capacity expansion such as those that are studied in this thesis. Least cost linear programming models are usually used such as mixed-integer linear programming. Stochastic programming has been used to factor in uncertainty but this method optimizes the solution over one period and does not factor in learning and flexibility. For instance, the capacity expansion plan may be optimized for the next twenty years though we there may be various changes in the system between now and then. Other techniques used include simulation methods such as scenario analysis. These simulate a system under different parameter assumptions but do not provide a basis for decision making.

In this section, I present a few studies that have used the different techniques in capacity expansion planning. I give various examples of the types of models used, highlighting the strengths and weaknesses of each. This discussion sets the stage for the description of the methodology that is used in this thesis in Chapter 3. An overall description of resource planning and decision making in the electricity sector is first provided to give some background on decision-making in the power industry. This background information is referenced in the description of the methods to be used in this thesis.

2.2 Resource Planning

Electricity resource planning is divided into four decision stages: long term, medium term, short term, and real time decision making. The highest level of decisions is made in the long term and the effect of these decisions ripple down to all other levels of decision making. Decisions for both generation and transmission expansion are made at this stage based on forecasts of future load demand. This thesis focuses on generation expansion only. Figure 2.1 shows the planning structure in electricity generation.

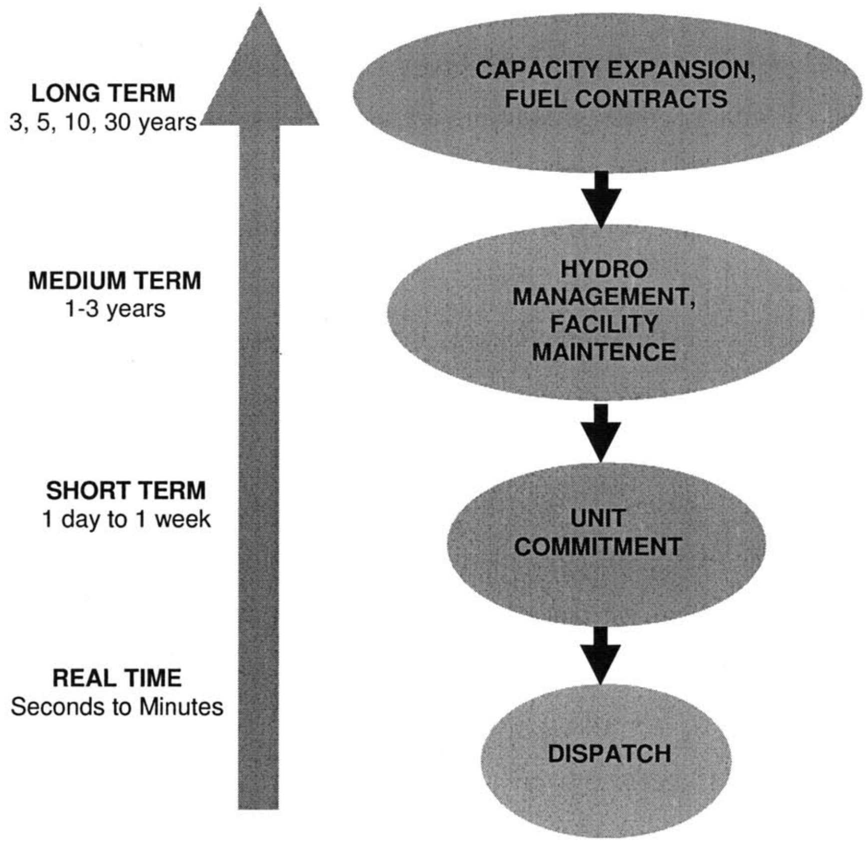

Figure 2.1: Resource Planning in Electricity Hierarchy (adapted from Gomez-Exposito, et. al, 2008)

In the long term, emphasis is on the generation capacity expansions and grid investment. In a deregulated market such as ERCOT, the goal of the generators is to maximize revenues and profits and lower all costs. Capacity expansion models generally take into account variables such as the demand growth forecast, technology alternatives and costs, price trends, and regulations (Hobbs, 1994). They however only consider the system technical constraints and specifications at a high level and use average conditions. Metaheuristic methods that are used in expansion planning for example only solve the optimization problem given demand and the costs of each technology. The uncertainties in these operational specifications have been overshadowed by the large uncertainties in the variables in the long term which are of more significant financial impact (Gomez- Exposito, 2008 *ed*). However, with the variability in wind and solar patterns in the short term it is necessary that expansion models that capture more resolution in the short and real time terms are used.

Contracts for fuel and maintenance scheduling are made in the medium term. For instance, steam turbines need 20 days of maintenance in a year (Gomez-Exposito, 2008). In a deregulated market, tasks also involve economic forecasts, and yearly budgets.

In short term and real time decision making, the goal is to minimize actual generation costs (Hobbs, 1995). The system operator makes these decisions and has the mandate to maintain system reliability and resource adequacy. Generation costs for fossil plants have high start up and shut down costs and these are taken into account in the unit commitment problem, where unit generation is determined by the plants' cost structure within hours or over a week. Electricity dispatch is then carried out with the unit commitment constraint. Electricity dispatch is a process by which the power generated by each unit connected to the grid is determined (Wollenberg, Wood, 2006). It is in this real-time period that the amounts of wind and/or solar generation available are forecasted more accurately. While the unit commitment problem has been included in some models, the inclusion of these short terms variability in renewable energy patterns is still being studied.

In this thesis, I propose to combine the objectives of long term and real term planning to establish a more robust capacity expansion model. The high resolution provided by the dispatch model can help inform capacity expansion models better than methods currently used. Table 2.1 is a summary of the goals of long and short term planning which the method used in this study intend to meet.

Table 2.1 Comparison of Capacity Expansion and Electricity Dispatch (Hobbs, 1995)

	Long Term	Short Term
Economic	Minimize the present worth of capital costs, operating costs, and outage cost	Minimize the variable cost of generation
Decision Variables	Resource amounts and timing, fuel sources, environmental control measures	Load carried by each generating unit and the amount of load curtailment
Constraints	Capacity limitations, along with requirements that generation be sufficient to meet customer demands, environmental regulation, financial and economic constraints	

The following is a review of the methods that have been used before in capacity expansion which I will synthesize and use in this thesis.

2.3 Review of Similar Studies

There are numerous methods that have been used to answer the question of future investment in generation considering various uncertainties. In the following subsections I will look at the most widely used methods which were used to generate the approach used in this study.

2.3.1 Optimization

Optimization methods in capacity expansion planning have the objective of selecting design capacities for generators by minimizing capital and operating costs of the system while meeting load and satisfying the physical constraints of the system in the long term (Malcolm et al, 1994). In the short term, optimization methods have the objective to meet demand while maintaining security and reliability in the system, as in dispatch models.

Common optimization methods used in capacity expansion are linear programs (LP). Linear programs are deterministic as the solution is based on the specific parameter values in the model. They do not consider uncertainty in these parameters. There are other LP methods such as mixed-integer linear programming (MILP) which address two parts; the short-term dispatching problem and the long-term objective of meeting demand over a period of time (Ku, 2003). The advantage of MILP over LP is that it optimizes discrete units whereas LP deals with continuous variables of the system (Majumdar et al, 1999). Despite this benefit from MILP, the result is still deterministic. LP methods usually have to be coupled with decision analysis to test out different parameters. An electricity dispatch model for example is deterministic. However, using it together with dynamic programming, for example, allows for the decision to be optimized against different sets of parameters.

Stochastic programming is used in capacity expansion models that include uncertainty. Though they have always been used in electricity power systems, stochastic models are now more employed in modeling intermittent renewable energy sources. A study by Castranouvo et al (2007) used Monte Carlo methods to capture the variability in wind. The model used also considered optimization hour-by-hour as proposed in this thesis to capture forecast more accurately. However, the expansion still produced a "hear-and-now" decision where a one-time decision is made over the period considered. In a paper by Garcia-Gonzales et al (2008), a stochastic model is used to incorporate uncertainties in wind patterns and electricity prices for use in the short term or day-ahead markets in Spain. A two-stage stochastic model is implemented (Garcia-Gonzales et al, 2008). This is called stochastic programming with recourse, where the decisions in the two stages are the same but have different probabilities (Growe et al, 1995).

2.3.2 Simulation

Simulation methods are used to experiment with different values of the parameters in the problem (Ku, 2003). These are especially useful when dealing with uncertainty where the range of possible outcomes can be explored. Most studies, even when using other methods of expansion, use simulations when they have uncertain variables. Monte Carlo simulations are a useful tool in evaluating different scenarios. Another common simulation tool is sensitivity analysis which analyzes the effect of a single variable (Mital, 2004).

Scenario analysis is a method used to compare a number of possible outcomes to select the optimal strategy. The aim of this method is to compare different parameters in related storylines, to see the differences between them rather than dwell on the results of one solution. Scenarios facilitate the results of varying assumptions, the range of possible futures, and trade-offs (Johnston et al, 2006). IEEE study by Linares conducted a power systems planning model using multi-criteria decision making and risk analysis for the Spanish electricity sector. A number of scenarios were generated focusing on uncertainties in the economy and environmental regulation. Different stakeholders and decision makers were then asked for their preferences and these were used to select the most robust strategy. Scenario analysis has to fulfill the objective of a specific stakeholder. In other words, the scenarios have to be run separately and then a decision is made using some external information. Examples of such models are

Decision trees are also a widely used simulation tool. They are useful in uncertainty analysis as they map out a range of possible outcome allowing for strategic decision making (de Neufville, 1990). Decision trees, like dynamic programming, can be used to model decisions made over multiple periods and are also used to analyze multiple uncertainties. Botterud et al conducted a study simulating capacity expansion decision for various generators in the Iberian market (Botterud et al, 2002). They use a decision tree to map the different scenarios for uncertainty in load growth, hydropower conditions, and competitors' expectations. An economic dispatch model is used to evaluate each of the scenarios and probabilities are assigned from available information. The approach in this thesis mimics this decision tree approach.

2.4 Flexibility

A study by Malcolm et al proposed using a "robust" model in expansion planning under uncertainty. A number of scenarios under different levels of demand uncertainty were considered. The objectives of the model used were the expected cost of the system over the different scenarios, the variance in the cost, and a term that penalizes deviations from feasibility were used. Robustness of the solution was then measured by varying the multipliers of the variables (Malcolm et al, 1994). Robustness gives the illusion that we can control an uncertain future. Malcom et al assert that the robust model can be used for various uncertainties, and they describe the solution as 'almost optimal' for any scenario. According to Richard de Neufville, "Robust design is passive way to deal with uncertainty. Flexible design is active way to deal with uncertainty." Flexible design allows that the decision made today incorporates uncertainty in such a way that the decision can be changed as knew knowledge is learnt. In this thesis, I use flexibility design which analyzes different technology performances over a range of varying future circumstances. This approach enables the system to avoid future downside risks while taking advantage of any opportunities that may arise (de Neufville, 2009).

In a study by Geenthal Mital, a real options approach was used to evaluate the expansion in hydropower. 'Real options' is a type of flexible design and a real option is the right to take action at a predetermined exercise price for a period of time (Copeland et al, 2001). Two options were analyzed; the size of the plant and the time that the plant should be built or deferring the build to observe electricity demand and increase certainty. Mital's thesis also compared this approach with more deterministic and irreversible approaches such as simple net present value (NPV).

NPV assumes that the decision is made today and all the cash flows are in today's dollar value and ignore that some decisions maybe made at a later time. Other deterministic methods mentioned in Mital's thesis are cost benefit analysis, life cycle costs, and internal rate of return. He concluded that the dynamic decision making provided by flexible design is more effective than the deterministic approaches and also was helpful for managing risk than expected values (Mital, 2004).

Reedman et al (2006) carried out a study that used a real options approach to model technology adoption under carbon price uncertainty for the Australian electricity sector. A mathematical program called CSIRO's Electricity Market model (EMM), was used to estimate the price of electricity until 2050 using drivers such as technological change and turnover of installed generating capacity. Technical specifications of the grid were considered including plant location and structure of the transmission network. The only uncertainty addressed in this study was the carbon price; scenarios were made based on when the carbon tax was put in place and also at what level the tax would be. Also, the scenarios focused only on thermal plants and did not include renewable energy sources which apply significantly to Texas. Using the real options model, they then evaluated which technologies would be invested in, and also when it would be most profitable for investors to build these plants. The EMM model evaluates the various scenarios from the short-term market bidding process, then the physical structure of the grid, and includes a platform to calculate the green house emissions (Redman et. al, 2006). Though this study does not include renewable generation, this approach is similar to that proposed for this thesis. It captures grid operations at high resolution and also includes flexibility in decision making.

2.5 Example Models

In this section, two examples of models that are currently used in expansion planning are described and critiqued. These models are the MARKAL and ReEDs models.

2.5.1 MARKet Allocation (MARKAL)

MARKAL is a capacity expansion model developed at the Brookhaven National Labs to conduct scenario analysis. MARKAL is a well recognized model and has been used in numerous studies for the Environmental Protection Agency. The most distinctive feature in MARKAL is that it is a systems' model, modeling the economy, energy, and the environment. It models existing and new technologies available for electricity generation based on sector-specific electricity demand (residential, commercial, industrial, and transportation), fuel prices, technology costs, and the environmental and operational constraints. It has a base case modeled into it by which all other scenarios are compared. It uses least cost optimization to compare different scenarios. The model was made to represent years from 1995 to 2030 and is optimized over the entire horizon (Johnson et al, 2006).

The ability to model capacity expansion as a function of the different sectors of the economy allows MARKAL to capture some feedbacks in the larger picture. However, it does not capture the stochasiticity of wind variation and instead uses average values for power generation. Moreover, results from MARKAL are from running individual scenarios are deterministic and not probabilistic. Finally, MARKAL is optimized over an entire 25 year period and does not allow for dynamic decision making as is proposed in this thesis.

2.5.2 Regional Energy Deployment System (ReEDs)

ReEDs was developed by the National Renewable Energy Lab (NREL). It was developed primarily to address issues such as carbon constrained scenarios, renewable portfolio standards, carbon taxes and caps which are of greatest significant today (Short et al, 2008). The deployment of renewable energies is therefore the major concern of this model.

It is a linear programming optimization model from 2006 to 2050 which minimizes the system wide costs of meeting demand and transmission. It is divided into twenty three 2-year periods and is optimized over each step. This gives more resolution in the optimization since shorted periods of time are considered. ReEDs is made for the US and is distinctive in that it is disaggregated along interconnects, NERC areas, RTOS, power control, and renewable energy supply. This disaggregation allows ReEDs to include the network though at a higher level than a dispatch model. Transmission costs are calculated based on the distance between the load and the generator. However, this is not a true representation of the actual network. Because of the focus on renewable energies, ReEDs has a detailed stochastic treatment of wind and solar power to capture the variability and intermittent nature of these sources.

ReEDs is a much more detailed model than MARKAL discussed in 2.5.1. Optimization is over shorter periods; it includes the network though at a higher level; and models the uncertainty in wind patterns. However, the results presented from ReEDS are for independent scenarios and are not probabilistic. Moreover, though there is more resolution in the optimization, a single decision is made through out. There is therefore no flexibility in the decision making over the 44 years considered. Also, the network is represented at a much higher level despite the disaggregation in the geographic areas.

2.4 Chapter Summary

There are numerous methods that have been used in capacity expansion planning. Most models used in this problem are optimization methods which are deterministic and do not include uncertainty. Scenario analyses are also conducted but these are presented independently and decisions cannot be determined quantitatively. Stochastic programming is a step up from deterministic optimization as it includes uncertainty. However, there is only one decision that is made despite the length of the period considered in the expansion period. Table 2.2 is a summary of the models that have been used in studies.

Table 2.2: Conventional Methods of Decision Making in Expansion Planning

Method	Draw Back
Deterministic Optimization	Ignores Uncertainty
Scenario Analysis	Scenarios are run separately and do not provide basis for decision-making
Stochastic Programming	Considers uncertainty but is not flexible

As stated, this thesis uses a synthesis of the various methods that are described above. I aim to use a dispatch model to capture the network operations more accurately. The dispatch model is an optimization model allocated generation to the units in the network while minimizing the costs. Using a Monte Carlo, I will model the variability in the wind and solar patterns. Finally, after running the different scenarios, I will use dynamic programming to evaluate them with the objective of maximizing the profits of the generation units. Chapter 3 describes in more detail, the methodology used in this thesis.

3.0 METHODOLOGY

The methodology used in this thesis is aimed at modeling the evolution of the generation network over the long term while incorporating short term dynamics. In the short term in particular, there is concern over the amount of wind energy a generator can produce given the season and the time of day. To the investor, this affects expected profits while, for the system operator, demand must still be met at all times. In capacity planning, the increase in renewable energy sources encourages the need to incorporate this short term concern. In addition to modeling the wind variability, the uncertainty in the costs of fuel and emissions prices necessitates the need to forecast investor costs more accurately than conventional models. The hypothesis is that the combination of methods used in this analysis is more rigorous than the conventional methods and therefore more useful in informing investor decisions.

Different future generation technology scenarios are developed and built into the ERCOT system. Using the generator characteristics of existing plants in the ERCOT region, costs for producing power for each generator were calculated. At this stage, the uncertain carbon and natural gas prices are imposed on the system. These costs are then used in a dispatch model to perform constrained optimization, which results in the allocation of generation to the units in the region. The profits made by each generator are then used to calculate the net present values of each of the technology scenarios that were assumed. In a decision tree, these scenarios were evaluated against each other to establish the scenario with the highest expected net present value.

The sections below detail each of the steps that have been summarized here. First I describe the uncertainties in question, and the scenarios that were investigated. I then detail how the system was modeled and then explain the cost model, the dispatch model, and finally the decision analysis.

3.1 Uncertainty Scenarios

The two uncertainties considered are the price of natural gas and the price of the carbon. The carbon price used in these scenarios ranges from \$0-\$50/ton of CO_2. This range is most commonly used in studies. The price of natural gas price used was based on the EIA's Energy Outlook for 2010. The high and the low are determined from the short term energy forecast

In the first stage of the decision tree (2010-2020), I assumed that the price of carbon is either 0 or low (\$50/ton of CO_2). Since there is currently no carbon price, it is reasonable to assume that in the period from 2010 to 2020, there may not be a price level established. Also, if there is to be a price placed, I assume that it starts off at a low level and potentially increases in the second stage.

Table 3.1 describes the scenarios that were considered in the first stage of the decision tree.

Table 3.1: Stage 1 Uncertainty Scenarios

Scenario	Description
1. Low Carbon Price and Low Natural Gas Price	Carbon Price = \$50/ton CO_2 Natural Gas Price = \$3/MMBTu
2. Low Carbon Price and High Natural Gas Price	Carbon Price = \$50/ton CO_2 Natural Gas Price = \$15/MMBTu
3. 0 Carbon Price and Low Natural Gas Price	Carbon Price = \$0/ton CO_2 Natural Gas Price = \$3/MMBTu
4. 0 Carbon Price and High Natural Gas Price	Carbon Price = \$0/ton CO_2 Natural Gas Price = \$15/MMBTu

In the second stage, I assume that there is for certain a price that has been placed on carbon. The price in this second stage is either low at \$25/ton of CO_2 or high at \$100/ton of CO_2. The natural gas price range is the same as in stage 1.

Table 3.2 is a summary of the uncertainty scenarios considered in the second stage of the decision tree.

Table 3.2: Stage 2 Uncertainty Scenarios

Scenario	Description
1. Low Carbon Price and Low Natural Gas Price	Carbon Price = \$25/ton CO_2 Natural Gas Price = \$3/MMBTu
2. Low Carbon Price and High Natural Gas Price	Carbon Price = \$25/ton CO_2 Natural Gas Price = \$15/MMBTu
3. High Carbon Price and Low Natural Gas Price	Carbon Price = \$100/ton CO_2 Natural Gas Price = \$3/MMBTu
4. High Carbon Price and High Natural Gas Price	Carbon Price = \$100/ton CO_2 Natural Gas Price = \$15/MMBTu

3.2 Determination of Technology Scenarios

From the uncertainty scenarios described in 3.1, I model eight technology scenarios, four for each year (2020 and 2030). I assume demand levels from those published by ERCOT in their Long Term System Assessment. These were available until 2019. I used an average growth of 2% per year to estimate the demand in both 2020 and 2030. Also, to calculate the amount of capacity that had to be built, I retired all plants that were fifty years or older. In addition, I assumed that ERCOT maintained a reserve margin of 12.5%. Table 3.3 is a summary of the state of ERCOT's generation capacity. Of importance is the amount of capacity that is needed to fulfill the demand in ERCOT while also replacing retired plants and maintaining generation adequacy.

Table 3.3: Derivation of New Capacity Needed

	2010	2020	2030
Available Capacity (MW)	85520		
Retiring Plants (MW)		15475.1	15028
Peak Demand (MW)		78964.32	96310
Peak Demand + 12.5% Reserve Margin (MW)		88834.86	108348.75
New Capacity Needed (MW)		**18789.74**	**34541.89**

A simple screening curve method as described in Stoft (2002) was used to determine the amount of each technology to be built. Starting with the amount of new capacity needed, I used screening curves to determine the amount of capacity that should be built from each of the competing technologies. The screening curve method is based on the equation 1 below:

$$\text{Screening Curve : Cost (\$/h)} = \text{Fixed Cost} + \text{Variable Cost} * \text{Generation} \qquad \textit{Eq 1}$$

The technologies considered were:

1) Pulverized Coal
2) Natural Gas Advanced Combined Cycle
3) Advanced Combustion Turbine
4) Wind Turbine
5) Solar Photovoltaic

These are considered as they are in the first stage and in the second stage, pulverized coal has a 90% CO_2 capture rate in one of the analysis.

To determine the scenarios, the costs of generating electricity are determined using the equation:

$$\text{Total Cost} = \text{Capital} + \text{Fuel Cost} + \text{O \& M} + \text{Emissions} \qquad \textit{Eq. 3.2}$$

(Mckearny, 2010)

where, "O&M" represents the operation and maintenance costs, "Fuel Cost " is the cost of the technology used by the fuel, and "Capital" is the cost of levelized or amortized cost of the technology. A fixed NO_x price and varying CO_2 prices are used for the emissions costs. Equation 3.2 is the expanded version of Equation 3.1 where capital costs represent the fixed cost; and fuel cost, O&M, and emissions costs make up the variable cost.

Capital cost data for the two time periods considered, 2010-2020 and 2020-2030, were obtained from a report by the Electricity Power Research Institute (EPRI) (EPRI, 2009). To amortize the capital cost, equation 3.3 is used where the initial investment is spread across the life of the generator.

$$\text{Fixed Cost} = \frac{\text{Capital Cost} \times \left(\frac{r}{1 - e^{-rT}} \right)}{cf \times 8760 \text{ hrs/year}}$$

Eq. 3.3

(Stoft, 2002)

where the fixed cost is the cost of construction spread out over the life of the plant, T, at a discount rate, r, of 10% (Stoft, 2002). An average capacity factor, cf, for the technology is used to spread the cost over actual power generated by the technology (EPRI, 2010).

The fuel cost is based on the forecasts provided by the EIA while the O&M costs are typical values assumed for the technology type. The emissions costs are calculated using the emissions rate assumed for the different technologies in the EPRI study.

Using the screening curves, I determine the least cost technologies for the required demand investment for each of the uncertainty scenarios described in section 3.2. The screening curves are linear with the fixed costs making up the y-intercept and the variable costs make up the slope of the curve. From the screening curves, I determined the size of generation capacity that should be provided by the technologies that were considered. Figure 3.1 is an example screening curve for the "low carbon, high natural gas price" scenario.

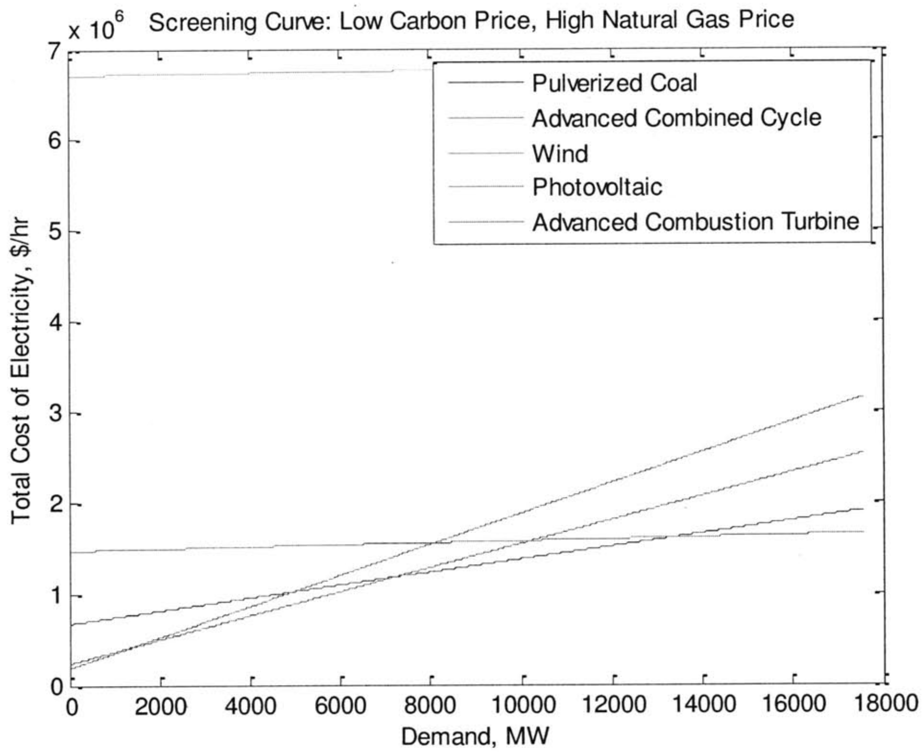

Figure 3.1: Low Carbon Price, High Natural Gas Price Scenario Screening Curves

From Figure 3.1 five technologies were compared against each other based on the costs of new capacity per hour. The scenario used in Figure 3.1 uses a low carbon price of $50/ton of CO_2 and a natural gas price of $15/MMBtu from the first stage. To read the screening curve, the technologies making the envelope on the curves have the least cost for the amount of production necessary. These are then taken as the generation portfolio. In the scenario in Figure 3.1, the generation portfolio comprises 1500MW of natural gas advanced combustion turbine, 5740 natural gas advanced combined cycle, 6000MW pulverized coal, and 4322MW of wind.

All other screening curves derived are given in Appendix 1. Table 3.3 gives a summary of the scenarios. The numbers in Table 3.3 represent each scenario as it was presented in Table 3.2

Table 3.4: Description of Scenarios

	Portfolio Mix	Short Description
Stage 1		
1	3000MW Advanced Combustion Turbine 14572 MW Advanced Combined Cycle:	'All Natural Gas 1' **83% CC, 17% CT**
2	1500 MW Advanced Combustion Turbine 5750 MW Advanced Combined Cycle 6000MW Pulverized Coal: 6000MW 4322MW Wind: 4322MW	'All fuels': **8% Gas CTs, 32% Gas CC, 35% Coal, 25% Wind**
3	2000 MW Advanced Combustion Turbine 3000 MW Advanced Combined Cycle 12572 MW Pulverized Coal	'Coal and Gas': **72% Coal, 17% CC, 11%CT**
Stage 2		
1	2500 MW Advanced Combustion Turbine 12177 MW Advanced Combined Cycle	'All Gas'
2	2000 MW Advanced Combustion Turbine: 5000 MW Advanced Combined Cycle: 7677 MW Pulverized Coal with 90% Capture	'Coal and Gas' **14% Gas CT, 34% Gas CC, 52% Coal w/ capture**
3	1000 MW Advanced Combustion Turbine: 9000 MW Advanced Combined Cycle 4667 MW Wind	'Gas and Wind' **68% Gas, 32% wind**
4	500 MW Advanced Combustion Turbine: 4500 MW Advanced Combined Cycle 3000 MW Pulverized Coal with 90% Capture: 6677 MW Wind	'All fuel' **4% Gas CT, 31% Gas CC, 20% Coal w/ capture, 45% Wind**

3.3 Modeling ERCOT

In 2009, ERCOT conducted a study (Analysis of Potential CO_2 Emissions Limits on Electric Power Costs in the ERCOT Region) that forecasted electricity prices in the region under the different CO_2 emissions targets proposed in the Waxman- Markey Bill. To conduct this study, ERCOT modeled the region as of 2009 with transmission improvements proposed for 2013, and also the Competitive Renewable Energy Zones (CREZ) which are to be completed in 2018 (ERCOT, 2009). Other minor improvements were also added onto the system to best represent its state by 2020. In terms of generation, a number of announced projects were added so as to meet demand by 2020. These announced projects can either be approved or rejected, so it is uncertain whether they will be built or not.

For the purposes of this thesis, I use the existing transmission network was used. However, I use different levels of new capacity as I also assume that plants that will be fifty years or older in 2020 and 2030 will be retired. This increased the amount of new generation that needed to be built. The screening curves described in section 3.2 were used to determine the type and size of the new generation. The new fossil generation this assumed to be built at bus locations of retired plants. Building new generators in these locations ascertains that we follow an already established trend; generators usually follow load centers. New wind plants were built on the new CREZ transmission lines which are in located in the western parts of the state where there is high potential for wind energy.

To construct the scenarios for 2020, fifty-year old plants were retired and new ones built in some of their locations. I ignore new generation that was added from announced projects. To build the 2030 system, the scenarios for 2020 were used as the base systems. This will be shown in more detail in Section 3.6, where the decision tree is presented.

3.4 Dispatch Model: PowerWorld

There are numerous ways in which a dispatch problem may be solved. Classic economic dispatch, also called merit order, is the simplest approach for power optimization and allocates generation to suppliers by minimizing the cost of generation. Other types of dispatch calculations take into account some constraints, such as losses in the power system (Galiana, 2009). Using an optimal power flow model allows the inclusion of multiple operational constraints in the optimization problem while still minimizing the generation costs. In planning, OPF can be used in economic analyses to calculate the costs of transmitting power over transmission lines (Wallenberg, 1996). In this thesis however, OPF is used to constrain the generation to the structure of the network. Limits on the transmission lines are disabled since there are network upgrades that will need to be built to take care of the new capacity.

There are three inputs to the OPF: marginal fuel costs, the electricity demand for a specific hour, and variable wind generation. The fuel costs are passed into PowerWorld, where the marginal cost of generation is calculated as shown in Equation 4.

$$\text{Marginal Cost of Generation} = \text{Heat Rate} * \text{Fuel Cost} + \text{O \& M Costs}$$

Eq. 4

The heat rate is the amount of energy input used to generate each MW of electricity. The components of Equation 4 (heat rate, fuel and operation costs) are detailed in Section 3.4.2. Only fossil fuel plants are included in the dispatch. Nuclear and renewable energy plants have a fixed amount of power production. Existing nuclear plants were assumed to always generate at maximum capacity. Wind energy was assumed to vary because of its intermittent nature and a full description of how this was modeled is given in Section 3.4.3. For every hour that was solved by the dispatch model, a different demand level for the year was assumed. The derivation of the demand level is detailed in Section 3.4.1 below.

Using the assumed heat rates, fuel costs, and O&M cost for all generators, the dispatch was solved using a DC-OPF. The case was solved in DC mode to avoid the complexities of the AC power flow. Solving in DC provides a linear solution to a very complex case making it faster to run. While the results are less exact in comparison to an AC solution, DC provides a fairly accurate approximation (Overbye et al, 2004). The power flow is solved for a single hour.

3.4.1 Electricity Demand

To run the OPF for the years 2020 and 2030, the electricity demand levels for the respective years had to be assumed. A sequential hour-by-hour forecasted demand profile for ERCOT was available for 2019. Using a 2% annual demand growth rate, hourly demand for 2020 and 2030 was calculated. From this data, load duration curves for the two years were constructed. Load duration curves are the annual demand ordered in terms of magnitude. The load duration curve is then discretized into 31 segments, and used to represent the years load. To obtain these 31 points, I sampled 1 hour of the load duration curve to represent 300 hours. I also included the peak and off peak points of the year. The thirty-one sample hours are 300 hours apart and include the peak hour and the off-peak hour. Figure 3.1 shows the approximations of the load duration curves.

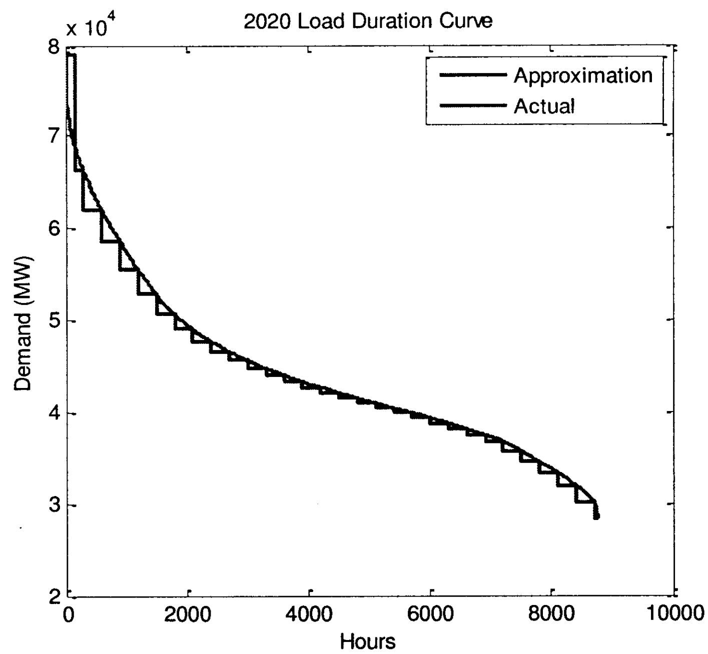

Figure 3.2 (a): Actual v. Approximate 2020 load Duration Curve

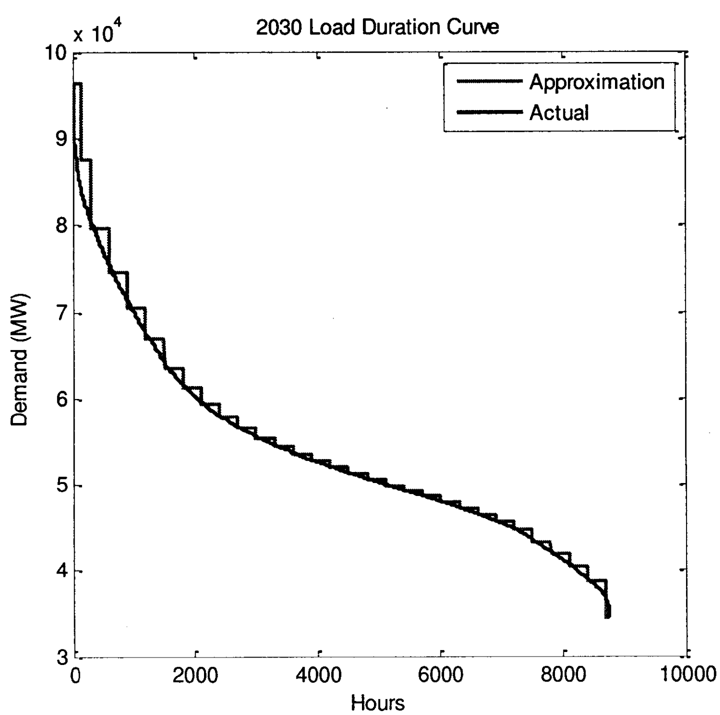

Figure 3.2 (b): Actual v. Approximate 2030 load Duration Curve

Using MatLab and PowerWorld's Simulator Auto, I solve each of the thirty-one hours at its demand level using DC-OPF. I solve this for all the technology scenarios described in section 3.2 under the uncertainty scenarios in section 3.1. Each technology has four auxiliary files containing the cost of generation (explained in 3.4.3). From MatLab, each demand level is passed to PowerWorld via SimuAuto and solved. Additionally, for new wind plants, generation is sampled for each hour given the season and the time of the day. This is explained in section 3.4.3. The results from PowerWorld are saved in Excel.

3.4.2 Generator Cost Model

Based on a 2009 steady state power flow case available from the ERCOT planning website, I imported generators in the region into an excel spreadsheet. These generators were assigned the ERCOT name and bus number. This information was then used to determine information for each generator from the Environmental Protection Agency (EPA) in the eGrid 2007 v1.1 database which contains information for each generator including the emissions rates. Plants were then matched using the Department of Energy's ORISPL codes which are assigned to all generating facilities in the country. Approximately 90% of generation was matched. Unmatched plants were mainly those that were added to ERCOT after 2005 when the eGrid data was prepared. The plant fuel types, heat rates, and emissions rates were used to calculate the total fuel costs of generation. All new plants were given standard characteristics based on a report by the Electric Power Research Institute: *Program on Technology Innovation: Integrated Generation Technology Options (EPRI, 2009).* Appendix 2 shows a summary of these characteristics.

Equation 5 is the calculation of the total fuel cost which is passed onto the dispatch model as shown in equation 4.

$$\text{Total Fuel Cost} = \text{Fuel Price} + \sum \text{Gas}_i \text{ Emissions Rate} * \text{Price}_i \qquad \textit{Eq.5}$$

where the fuel price depends on the generator technology, and i takes on the values CO_2, NO_x, and SO_2. This calculation does not include the heat rate; the heat rate is added separately in the cost model used in the dispatch model to calculate the generator marginal cost. Base prices of \$500/ton of SO_2 and \$2000/ton of NO_x are used for SO_2 and NO_x respectively.

I generated a csv file from the excel spread sheet which I then turned into at auxiliary file; the readable format for PowerWorld. The auxiliary file contains the fuel cost, heat rate, operations and maintenance costs, and other plant specifications.

3.4.3 Wind Distributions

Wind output data for years 2007 to 2009 are available from ERCOT. Using the hourly generation for these years, I used Matlab to first group them by season based on the month, and then by time, based on the hour of the day. The twenty-four hours of the day were divided into two with hours from midnight to noon comprising the "Night" and hours from noon to midnight comprising the "Day". I created eight separate data sets representing each of the four seasons, and the two times of the day. I then fit the data for each season/time-of-day combination to a Weibull distribution. The Weibull distribution has been used to forecast many natural phenomena including wind speeds. It is also commonly used for studying wind energy patterns (Justus et al, 1977). Here, capacity factors of wind to represent wind energy were used. The capacity factor is the amount of actual generation as a fraction of the total generation capacity of a plant calculated over a set period of time. Figure 3.2 shows the Weibull distribution of wind output in the ERCOT region for the three years from 2007 to 2009.

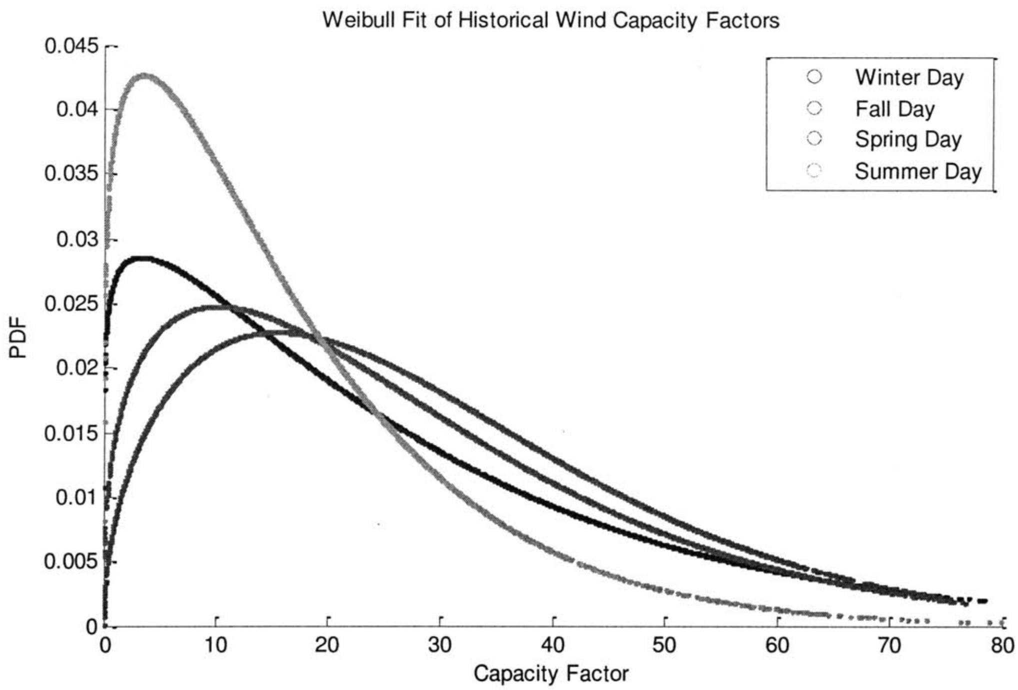

Figure 3.3 (a): Weibull Distributions of Wind for all the Seasons during the Day

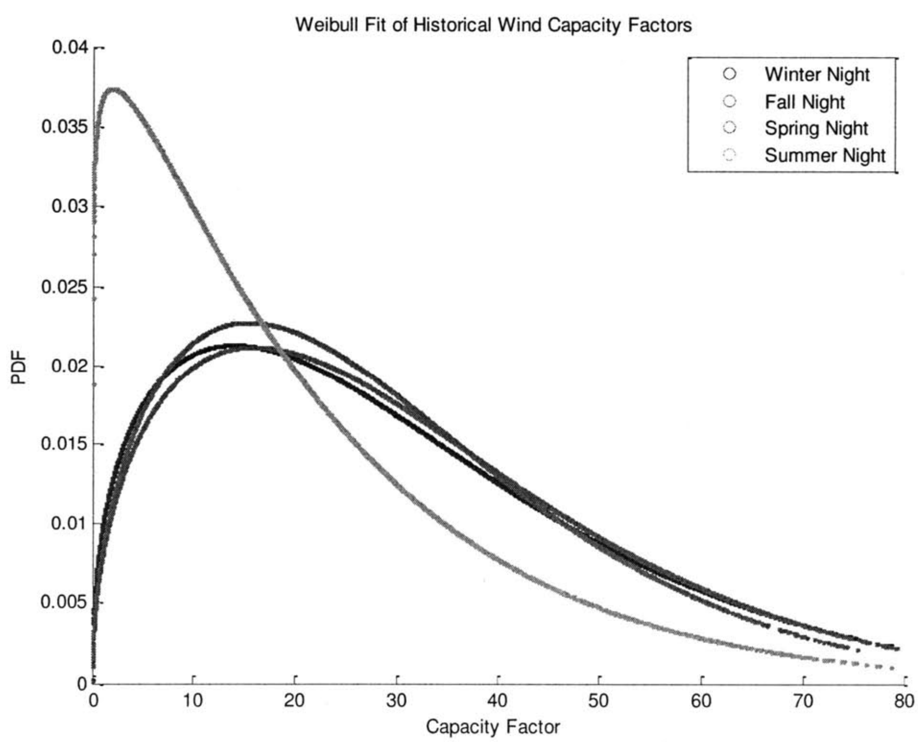

Figure 3.3 (b): Weibull Distributions of Wind for all the Seasons during Night Time

To perform a Monte Carlo simulation using the distributions in figure 3.2, I used Latin hypercube sampling to draw random variables that represent the full distribution spectrum. Three equally spaced probability fractiles were used: 0.25, 0.5, and 0.75. I used the inverse of these probabilities for the eight Weibull distributions as the sample of possible capacity factors. A Monte Carlo was then performed on the sample for every hour that was run. From the thirty-one hour sample of the load duration curve, I used the season and time of these hours to determine which of the Weibull distributions in figure 3.2 would be used.

To determine the generation of the wind plants, the randomly sampled capacity factor was used to calculate their actual power production. These values were then passed as non-dispatchable generation to PowerWorld where the OPF was solved. For each hour, the wind capacity factors were sampled three times, and the OPF solved thrice. An average of these three runs of varying wind generation was used to represent the hour.

3.5 Model Output

The output from the model is total production cost per hour for each of the generators. The sum for all the units gives the system hourly costs. Each sample hour is then multiplied out with the number of hours that it represents in the load duration curve to give the annual costs of generation.

The costs are calculated for the entire system. The present value of costs is then taken with the capital and a discount rate of 5% is used. The objective is to find the technology mix with the socially optimal output.

3.6 Decision Analysis

The dispatch model is a linear program which provides gives an optimal solution for a given set of parameters. However, since we cannot predict the future, these parameters can take on a number of variables. Dynamic programming is therefore used and it is based on the concept of enumeration which means that all possibilities are evaluated (de Neufville, 1990). Dynamic programming is used in this thesis to provide decision analysis. Decision analysis is a method used in strategic decision making which allows for the quantitative analysis of decisions given various. The objective for both the system operator and the investors is to achieve a technology mix with the lowest cost.

In this thesis, a two-stage decision tree is used for the two years, 2020 and 2030. Decisions for what generation technology to build to meet 2020 demand are made in 2010 while the decisions to meet 2030 demand are made in 2020. The uncertainties in the tree are the natural gas price and the carbon price. Each of the technology scenarios designed in 3.2 were then evaluated under the four different states of uncertainty at each stage of the tree. These states are described in table 3.3 for the two decision stages.

Table 3.5 (a): Stage 1 Decision Tree States

States	Definition
State 1	No Carbon Price, Low Natural Gas Price
State 2	No Carbon Price, High Natural Gas Price
State 3	Low Carbon Price, Low Natural Gas Price
State 4	Low Carbon Price, High Natural Price

Table 3.5 (b): Stage 2 Decision Tree States

States	Definition
State 1	Low Carbon Price, Low Natural Gas Price
State 2	Low Carbon Price, High Natural Gas Price
State 3	High Carbon Price, Low Natural Gas Price
State 4	High Carbon Price, High Natural Price

Using the decision tree, each of the paths that can be taken by technology scenarios was evaluated. At each stage, the path with the highest expected profit across the scenarios was established given varying probabilities between the states. Finally, the path giving the highest expected profit was calculated.

The results of the methodology explained here are given in Chapter 4. Additionally, analyses done on these results are carried out and illustrated.

3.6 Chapter Summary

To answer the question of what technology mix will be adopted in the future in ERCOT, I built a number of scenarios using screening curves and different prices of carbon and natural gas. These scenarios assumed that the expected demand levels in both 2020 and 2030 are met through investment. I assumed a 12.5% reserve margin for adequacy and reliability. Thirty-one equally spaced hours in the load duration curves were taken to represent the entire year for both 2020 and 2030. Using expected costs of technologies and fuels, I ran a dispatch model, Power World for each of the scenarios, which allocated generation to the different units in the system. The results from running these representative hours in the dispatch model were the amount of generation from each unit and the marginal cost of generation. The sum of these gave the hourly costs of generation. I then used a decision tree to evaluate between the different scenarios. The results of this analysis are reported in Chapter 4.

4.0 ANALYSIS

In this chapter, I present the results of the study with the goal of providing the expected path of technology evolution. A dynamic programming model was developed to evaluate the performance of alternative capacity expansion scenarios under uncertainty in future carbon prices and natural gas prices as described in Chapter 3. In efforts to clearly communicate the results, I present the results of the decision model using several different visualization approaches. First, I report the results from the decision model in a value at risk and gain (VARG) curve. A VARG curve compares the outcomes of each of the scenarios based on a cumulative distribution. I then show the result from solving the decision tree for the expected present values of costs. First I assumed equal probabilities for each uncertainty state. In addition, I present the result from running sensitivities on the probabilities. Finally, I present the implications of these results on the system; specifically I show the possible paths given the decision made in either period.

Two sets of results are presented here. First, I consider the scenarios as they are described in Chapter 2 and then in the second set, I investigate the resulting technology portfolio in the event that Carbon Capture and Storage (CCS) is not available in 2030. The first section presents an example from simulating a technology scenario within the ERCOT system as described in Chapter 3.

4.1 Model Illustration

In this section, I present an example load duration curve for 2030 to show the hourly variations of the generation given the costs of running the generators, wind variability and the demand levels. The scenario assumes the "All Gas" scenario in the first period, and the "Wind and Gas" in the second period. For each hour, the average generation per technology for three instances with varying wind is shown. In a dispatch mode, the hourly portfolios are filled by the least cost available technologies. The load duration curve is made up of 31 sample hours that were used to represent a year time-scale as described in section 3.4.1.

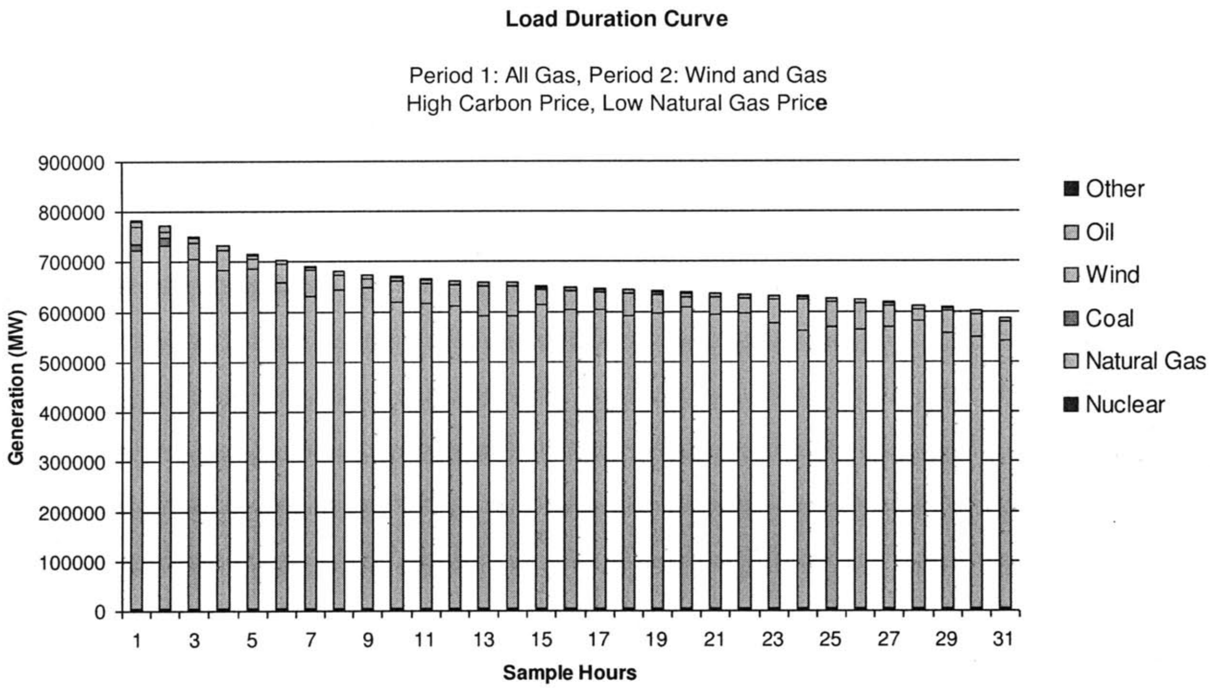

Figure 1

Figure 4.1: Load Duration Curve Showing Hourly Fuel Mix for the All Gas-Wind and Gas Scenario

In Figure 4.1 a picture of the demand levels and the fuel mix is shown for each of the 31 hours. The variation in the wind availability is also captured. Nuclear and "Other" fare non-dispatchable and therefore provide base-load generation. In this simulation, a high carbon price and a low natural gas price are assumed. For low demand hours, natural gas provides the generation depending on the amount of wind generation available. For the higher demand hours, coal and oil provide some generation to fulfill the demand. In spite of the high cost of coal and oil as a result of the carbon price, these technologies may become competitive depending on the resources available.

4.2 Considering CCS

In the first analysis, I consider the technology scenarios as designed in Chapter 2 and in 2030, CCS is available for the new pulverized coal plants.

4.2.1. Value at Risk and Gain Curve (VARG)

Using dynamic programming allows for flexibility in decision making over time. The motivation behind adding flexibility to an investment is to avoid downside risk while capturing the upside gains (Cardin et al., 2007). Value at Risk and Gain curves are usually used to evaluate investment choices in large physical systems and also for financial analysis. A VARG curve is another name for a cumulative distribution function. VARG curves are used to show the value of flexibility given a number of investment choices. It stresses the downsides and the upsides. An advantage of VARG curves is that one can visually compare all the design options. Figure 4.2 shows the VARG curves for each of the four decision scenarios.

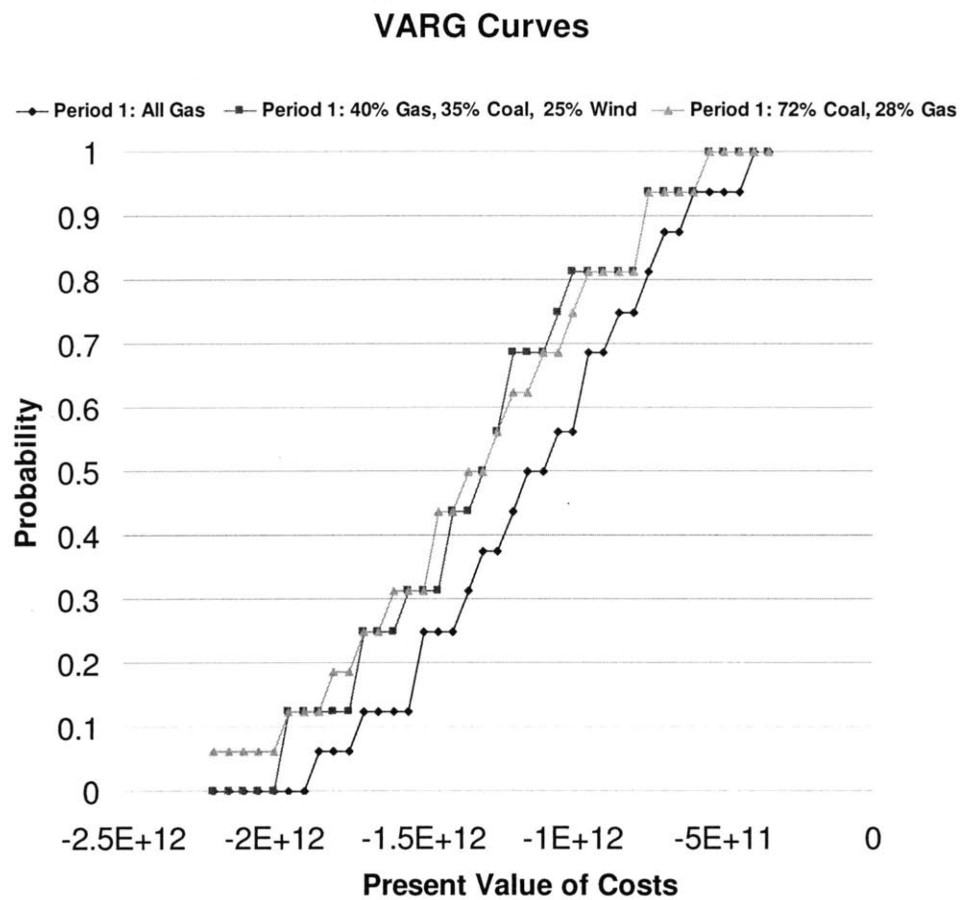

Figure 4.2: Cumulative Distribution Function of Present Value Costs for Decision Scenarios

Figure 4.2 shows the VARG curves for all the period 1 strategies, which are the three technology portfolio scenarios. To interpret the VARG curve, the right-most curve has the lowest present value cost when evaluated for a given probability level. From the results in Figure 4.2, each of the three scenarios has the least cost at some part of the VARG curve. The bottom end of the VARG curves shows which of the scenarios has the most risk, while the top end shows the most valuable (lowest cost) scenario. Table 4.1 shows the P_{10} and P_{90} read from each of the VARG curves in Figure 4.2.

Table 4.1: P_{10} and P_{90} Present Value Costs With CCS

Scenarios	P_{10}, \$ (x10^{12})	P_{90}, \$ (x10^{12})
1. All Gas (83% CC)	1.6	0.6
2. 40% Gas, 35% Coal, 25% Wind	2.0	0.8
3. 72% Coal, 28% Gas	2.0	0.8

The highlighted entries in Table 4.1 show the scenarios that lead to the lowest costs when evaluated at P_{10} and P_{90}. P_{10} gives the value at risk, showing that there is a 10% chance that the costs will be higher than the present cost when the probability is 10%. Similarly, P_{90} is the value at gain, which shows that there is a 10% chance that the costs will be lower than the present cost. The "All Gas" scenario is also the best solution when evaluated at any probability.

4.2.2 Decision Tree (Dynamic Programming)

In this section, I present the results of solving the decision tree for the lowest possible expected present value of costs. The assumption in the decision tree is that there is an equal chance between the states; probabilities of 0.5 are assumed for all uncertainties. Given that we currently have no knowledge of the probabilities, it is fair to assume a 50/50 chance between the uncertain variables. Figure 4.3 is a snapshot of the branch of the optimal solution under these conditions.

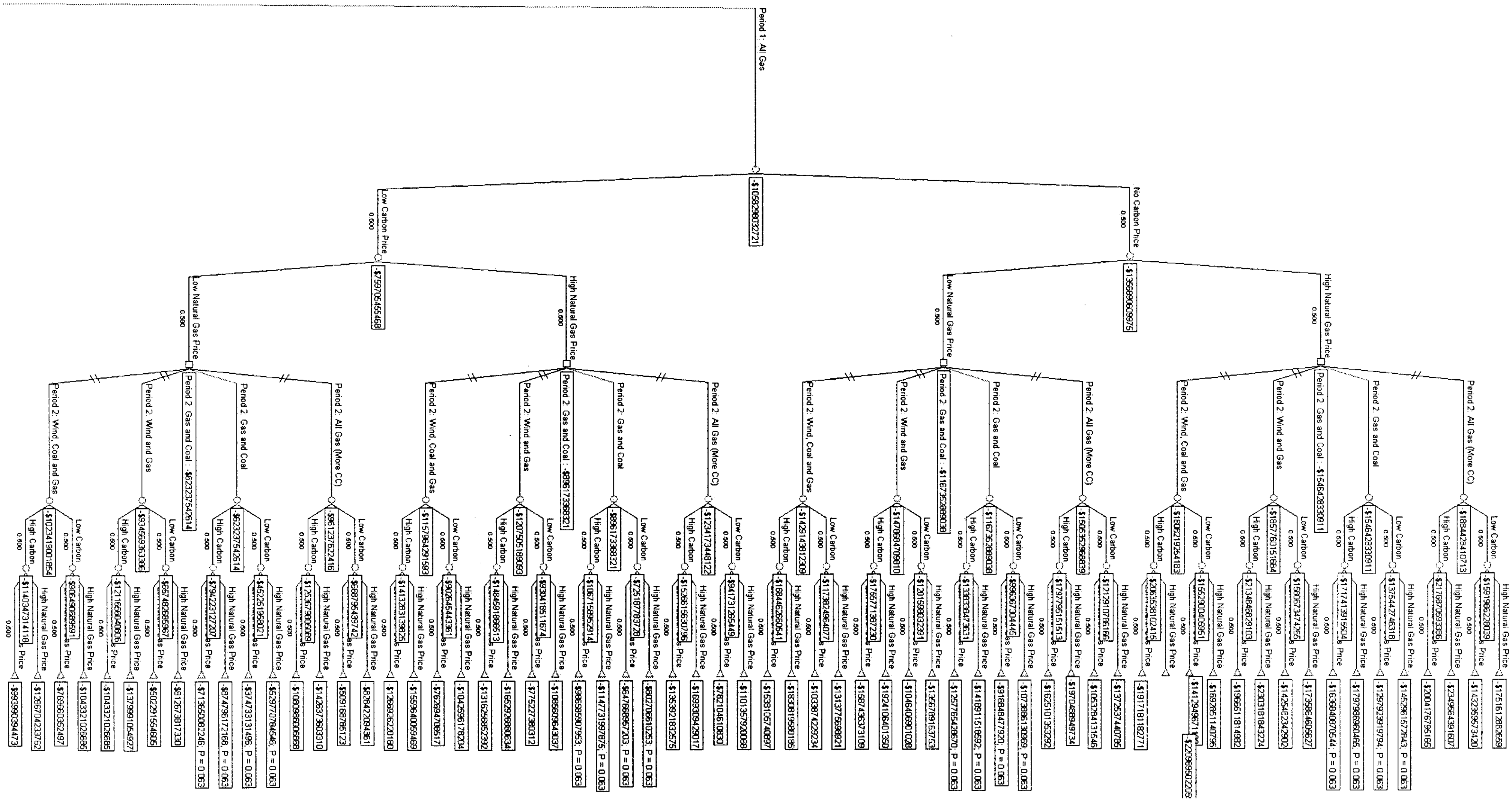

Figure 4.3: Snapshot of Decision Tree Showing the Optimal Scenarios in both Periods

4.2.3 Sensitivity Analysis

Sensitivity analysis is a process for investigating an optimal solution under different conditions or formulations of the problem (de Neufville, 1990). In this study, I investigated the effect of varying probabilities on the optimal solution. I used a high probability of 1 and a low of 0 with 20 intervals. The results indicate the scenario that provides the lowest cost on the system for given set of probabilities. The prices used for natural gas price are a high of \$15/MMBtu and a low of \$3/MMtu. For CO_2 the price can either be 0 or \$50/ton of CO_2 respectively.

4.2.3.1 Decision for 2020

The first sensitivity analysis performed was to establish the effect of the probability levels on the 2020 decision. Figure 4.4 is the result of this analysis.

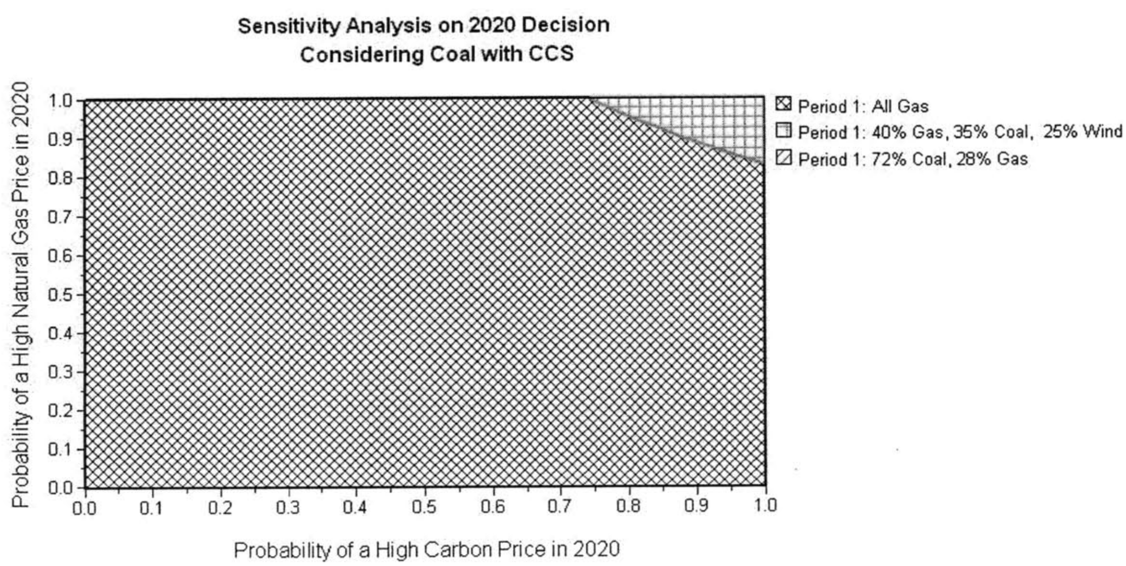

Figure 2

Figure 4.4: Sensitivity Analysis on Natural Gas and Carbon Prices in Period 1

From Figure 4.4, the "All Gas" scenario has a higher likelihood of providing the optimal solution. As the probability of a high carbon price increases beyond 0.75, the "Coal, Gas, and Wind" scenario becomes optimal. The corresponding probability of a high natural gas price is above 0.8. At this point, the combination of the high carbon price and the high natural gas price make the "All Gas" more expensive than the "Coal, Wind, and Gas" scenario. However, the "Coal, Gas, and Wind" scenario also contains expensive coal, and expensive gas in this region, and this explains the slope and the size of this region. The "Coal and Gas" scenario is not competitive given the prices of gas and carbon.

4.2.3.2 Decision for 2030

To analyze the 2030 decision, I performed conditional sensitivity analysis where I tested the effect of varying probabilities on the uncertainties in the second period. This analysis is conditional on the decision that would have been made in 2020. Moreover, the results are also dependent on the uncertainty state that 2020 could be in. The prices used for natural gas price are a high of \$15/MMBtu and a low of \$3/MMtu. For CO_2 the high and the low are \$25/ton and \$100/ton of CO_2 respectively.

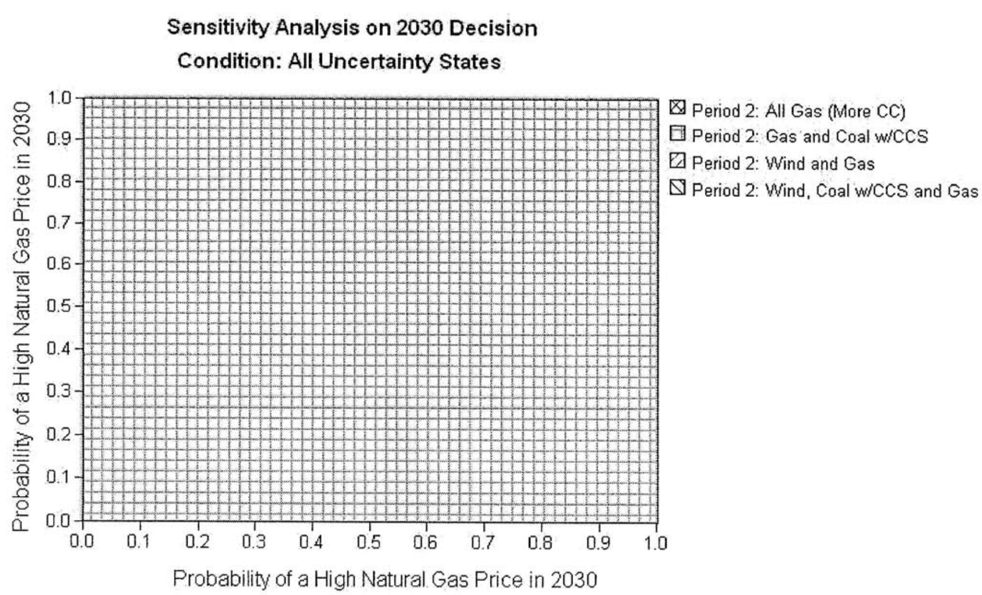

Figure 4.5: Sensitivity Analysis on Natural Gas and Carbon Prices in Period 2

In the second period of the decision tree, regardless of the probabilities, the "Gas and Coal with Capture" scenario is the optimal solution. Besides the high capital costs in pulverized coal with 90% capture and the high heat rate, the costs of coal are significantly reduced. In the model, a new coal plant produces powers at \$2.9/MMBtu under a \$25/ton of CO_2 and \$5.7/MMBtu under a \$100/ton CO_2 price.

Because of the uncertainty in the capital costs of carbon capture and storage, I did a sensitivity analysis on the capital costs. In the base case a price of \$4,435/KW is used for 90% capture. This analysis was dependent on the fuel type that would have been built in 2020. Assuming that the "Wind, Coal, and Gas" scenario is chosen, I found that the CCS would have to cost as least \$7,500/KW so that another scenario would be competitive.

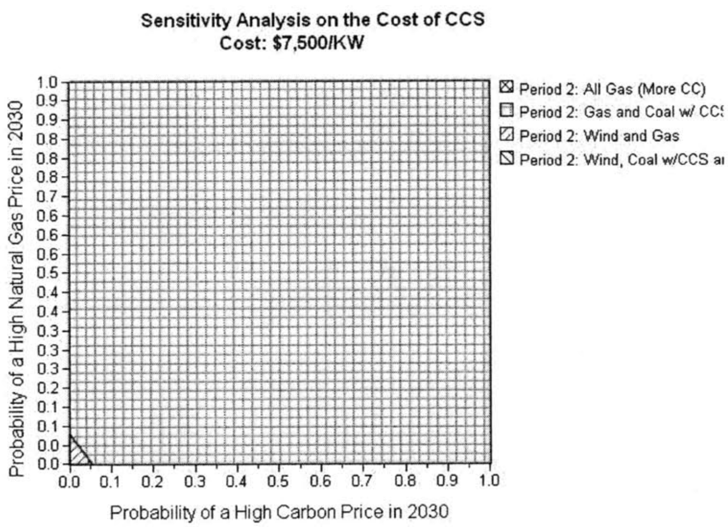

Figure 4.6: Sensitivity Analysis for 2030 given CCS costs \$7.500/KW

Figure 4.6 shows that with a cost of \$7,500/KW, the "Wind and Gas" scenario becomes competitive on the condition that the probabilities of both a high natural gas price and high carbon price are close to zero. The "Wind and Gas" is the second cheapest option once CCS is introduced as shall be illustrated in section 4.3.

Assuming instead that the dominant "All Gas" scenario is built, a much higher price of at least \$17,300/KW for the CCS would allow competition for CCS.

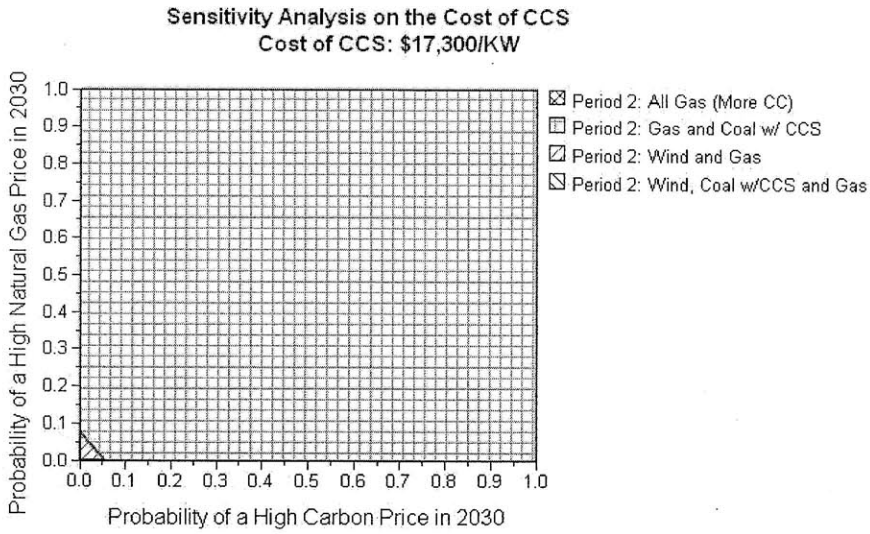

Figure 4.7: Sensitivity Analysis for 2030 given CCS costs of $17,300/KW

Figure 4.7 shows the competing technology scenarios as a price of $17,300/KWh of CCS considering potential decisions in 2020. Again, the "Wind and Gas" scenario is competitive given that the probabilities for both a high natural gas price and a high carbon price are close to zero.

4.2.4 Technology Evolution

From the results in the **decision tree** shown in section 4.2.1, the optimal solution in 2020 is the "All Gas" scenario. The optimal solution for the second period is the "Gas and Coal with CCS" scenario. I chose to present the technology evolution in terms of the decision tree because given that we currently do not know how the probabilities will play out, it is fair to assume equal likelihood between the uncertainties. Figure 4.8 shows the evolution of the composition of the ERCOT system from 2010 to 2020.

4.2.4.1 Generation Portfolio Evolution (2010 -2020)

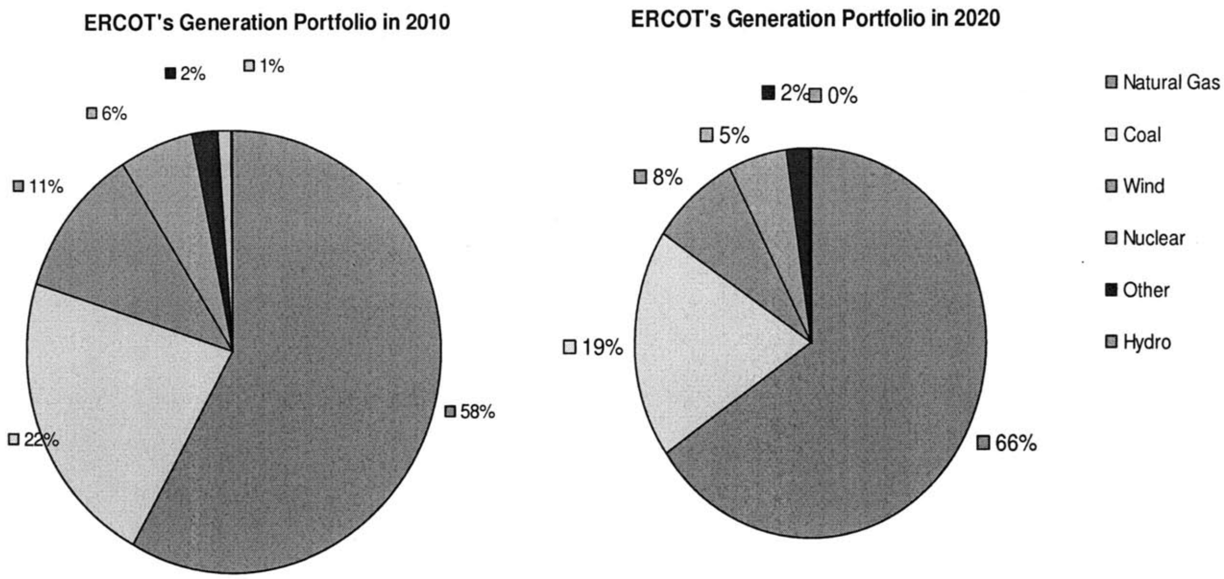

Figure 4.8: Evolution of Technologies between 2010 and 2020 (All Gas)

The changes in fuel composition are dependent on two main reasons; the retiring of old plants, and also the increase in new plants to meet demand. In 2020, the percentage of natural gas in the system increases by 8%. Coal and wind drop by 3% each. All other technologies are unchanged in absolute terms. All hydro generators in ERCOT will be over fifty years old in 2020, and therefore they are all retired.

4.2.4.2 Portfolio Evolution (2010 -2020)

Here, I compare the fuel types in ERCOT in 2030 on the condition that the generation evolves as shown in 4.2.4.1. The optimal solution for the second period is the "Gas and Coal with CCS" scenario. Figure 4.9 shows the compositions of the resulting when this scenario is assumed.

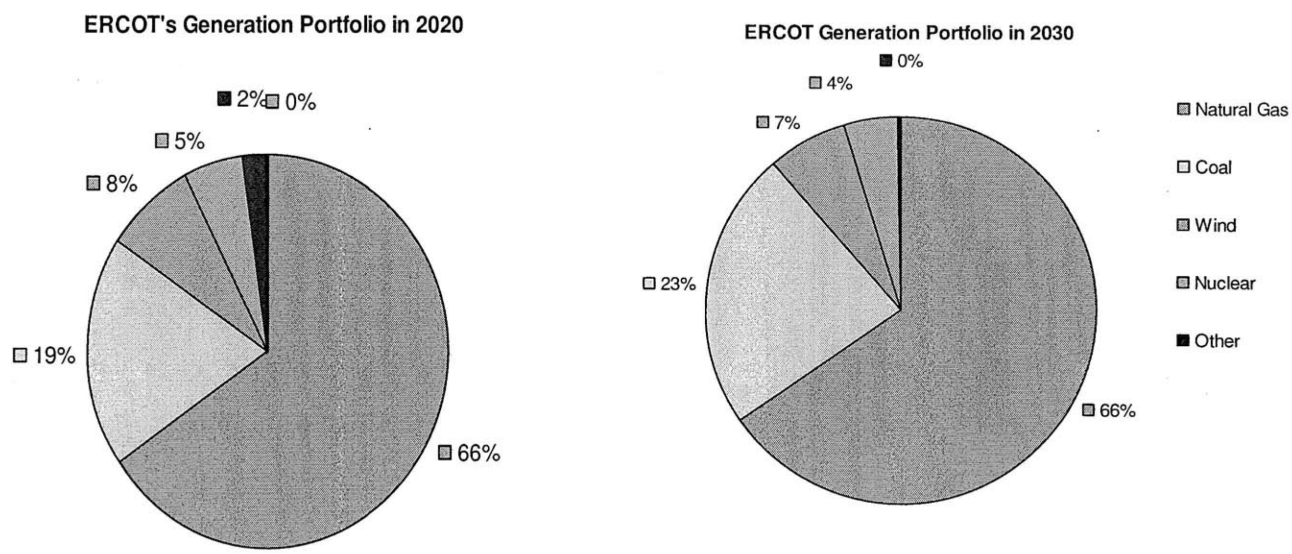

Figure 4.9: Evolution of Technologies between 2020 and 2030

The percentage of natural gas in the system remains constant while coal increases by 4%. Wind drops by 1%.

4.3 Without CCS

In the second analysis, I consider the technology scenarios as designed in Chapter 2 though in 2030, CCS is not available for the new pulverized coal plants.

4.2.1 Value at Risk and Gain Curve (VARG)

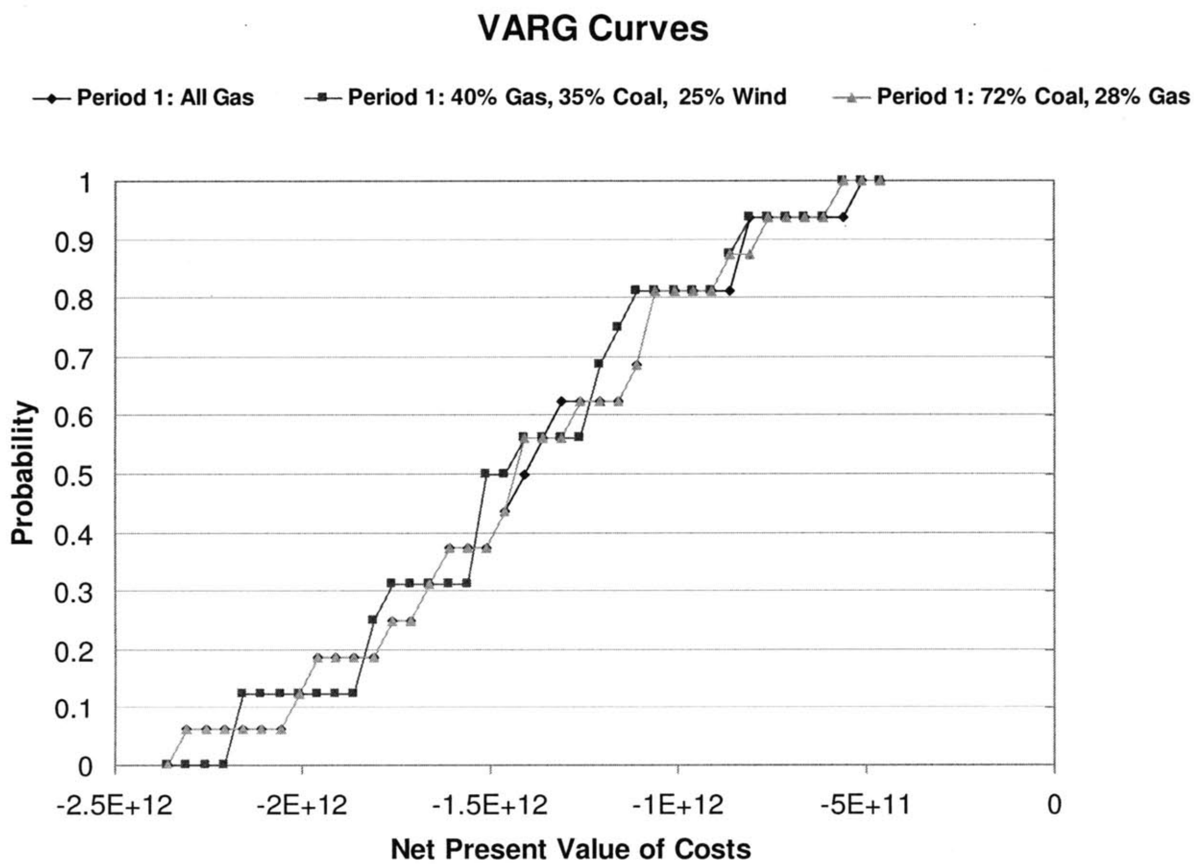

Figure 4.10: Cumulative Distribution Function of Present Value Costs for Decision Scenarios

Figure 4.10 shows the VARG curves for all the period 1 strategies, which are the three technology portfolio scenarios. The "Gas, Coal, Wind" scenario avoids the most risk, and the "All Gas" scenario captures the most gain. To provide a more comprehensive analysis of the VARG curves, I compared the curves at different probability levels. Table 4.2 shows the present value costs of all the design option evaluated at probabilities P_{10} and P_{90} which are commonly used in such analyses.

Table 4.2: P_{10} and P_{90} Present Value Costs Without CCS

Scenarios	P_{10}, \$ ($x10^{12}$)	P_{90}, \$ ($x10^{12}$)
1. All Gas (83% CC)	2.01	0.81
2. 40% Gas, 35% Coal, 25% Wind	2.16	0.82
3. 72% Coal, 28% Gas	2.01	0.76

The highlighted entries in Table 4.1 show the scenarios that lead to the lowest costs when evaluated at P_{10} and P_{90}. P_{10} gives the value at risk, showing that there is a 10% chance that the costs will be higher than the present cost. Similarly, P_{90} is the value at gain, which shows that there is a 10% chance that the costs will be lower than the present cost. The 'All Gas' and "Coal and Gas" scenarios avoid more risk and the "Coal and Gas" captures the most value of gain (lowest costs). Overall, the "Coal and Gas" scenario performs best when the options are evaluated at P_{10} and P_{90}. However, we can expect different results at other probability levels. The sensitivity analysis in the following section gives a fuller picture of the effect of different probabilities.

4.3.2 Decision Tree (Dynamic Programming)

Here, I present the results of solving the decision tree for the lowest possible expected present value of costs. The assumption in the decision tree is that there is an equal chance between the states; probabilities of 0.5 are assumed for all uncertainties. Given that we currently have no knowledge of the probabilities, it is fair to assume a 50/50 chance between the uncertain variables. Figure 4.11 is a snapshot of the branch of the optimal solution under these conditions.

From the decision tree, the optimal solution in the first period is the "All Gas" scenario. Assuming that this is the decision made in the first period, in the second stage, the optimal solution under all the four states is the "Wind and Gas".

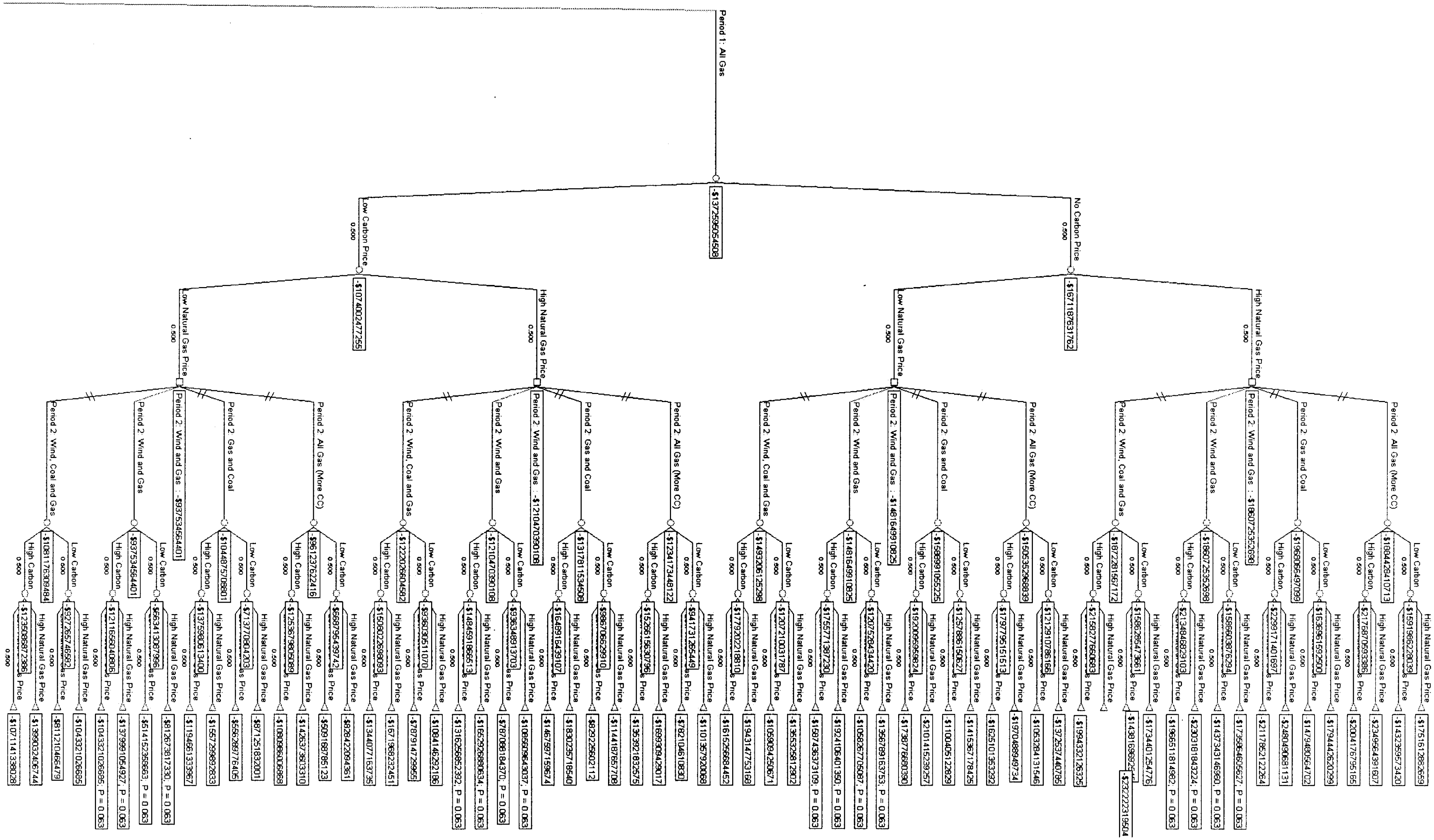

Figure 4.11: Snapshot of Decision Tree Showing the Optimal Scenarios in both Periods

4.3.3 Sensitivity Analysis

Similar to 4.2.1.3 I conducted a sensitivity analysis on the decision tree variables.

4.3.3.1 Decision for 2020

Here I performed a sensitivity analysis on the 2020 decision. Figure 4.12 is the result of this analysis.

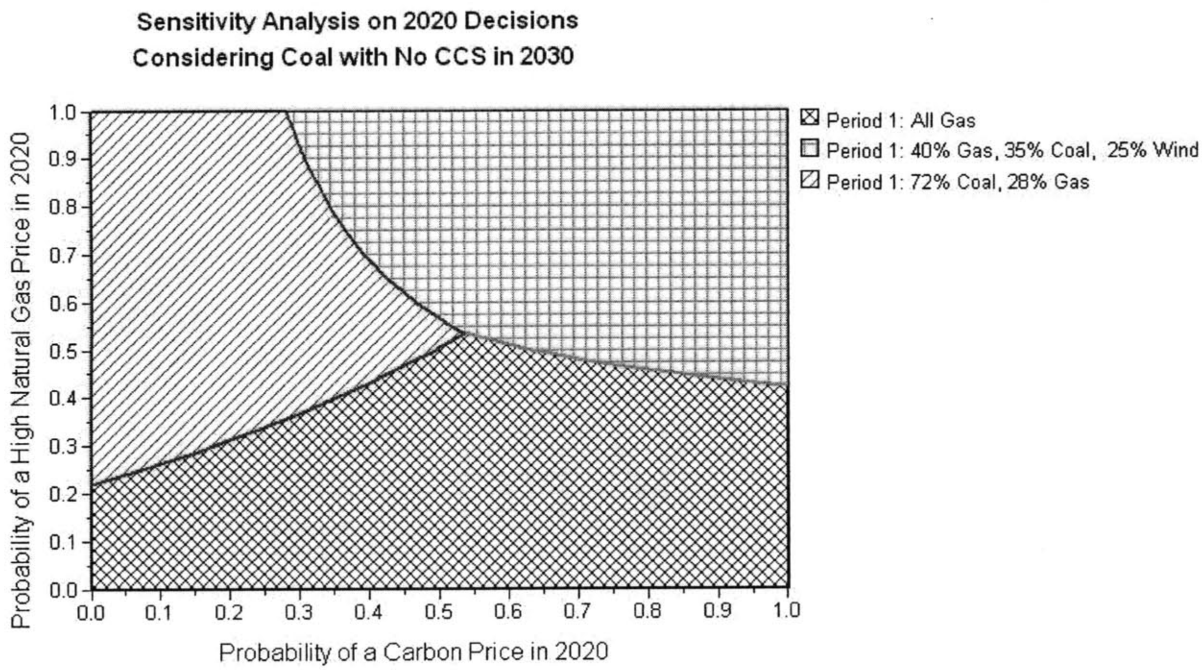

Figure 4.12: Sensitivity Analysis on Natural Gas and Carbon Prices in Period 1

From Figure 4.12, the decision is highly probabilistic; each technology scenario is optimal for some combination of the probabilities of the uncertainties. If the probability of a high natural gas price is below 0.2, the optimal choice is the "All Gas" scenario regardless of the carbon price. As the probability of a high gas price increases beyond 0.2, and the probability of the carbon price is below 0.3, the "Coal and Gas" scenario becomes optimal. This scenario has ore coal and less gas than the other scenarios and is therefore less susceptible to the price of natural gas. From a probability of a high carbon price of 0.3, the effect of the high natural gas price is displaced by the carbon price and as the probability of a carbon price continues to increase, the "Gas, Coal, and Wind" scenario becomes optimal. With wind as part of it, this scenario is less vulnerable to both the high natural gas price and the high carbon prices than the other scenarios. With a high likelihood of a carbon price (beyond 0.5) and as the probability of a high gas price decreases below 0.5, the "All Gas" scenario again becomes optimal again.

4.3.3.2 Decision for 2030

To analyze the 2030 decision, I performed conditional sensitivity analysis where I tested the effect of varying probabilities on the uncertainties in the second period. This analysis is all conditional on the decision that would have been made in 2020. Moreover, they are dependent on the state in which 2020 would have been, for example "no carbon price, high natural gas price". The prices used for natural gas price are a high of $15/MMBtu and a low of $3/MMtu. For CO_2 the high and the low are $25/ton and $100/ton of CO_2 respectively.

Condition 1: "All Gas" Scenario

The results in 4.13(a) are made on the assumption that the "All Gas" decision is made in 2020.

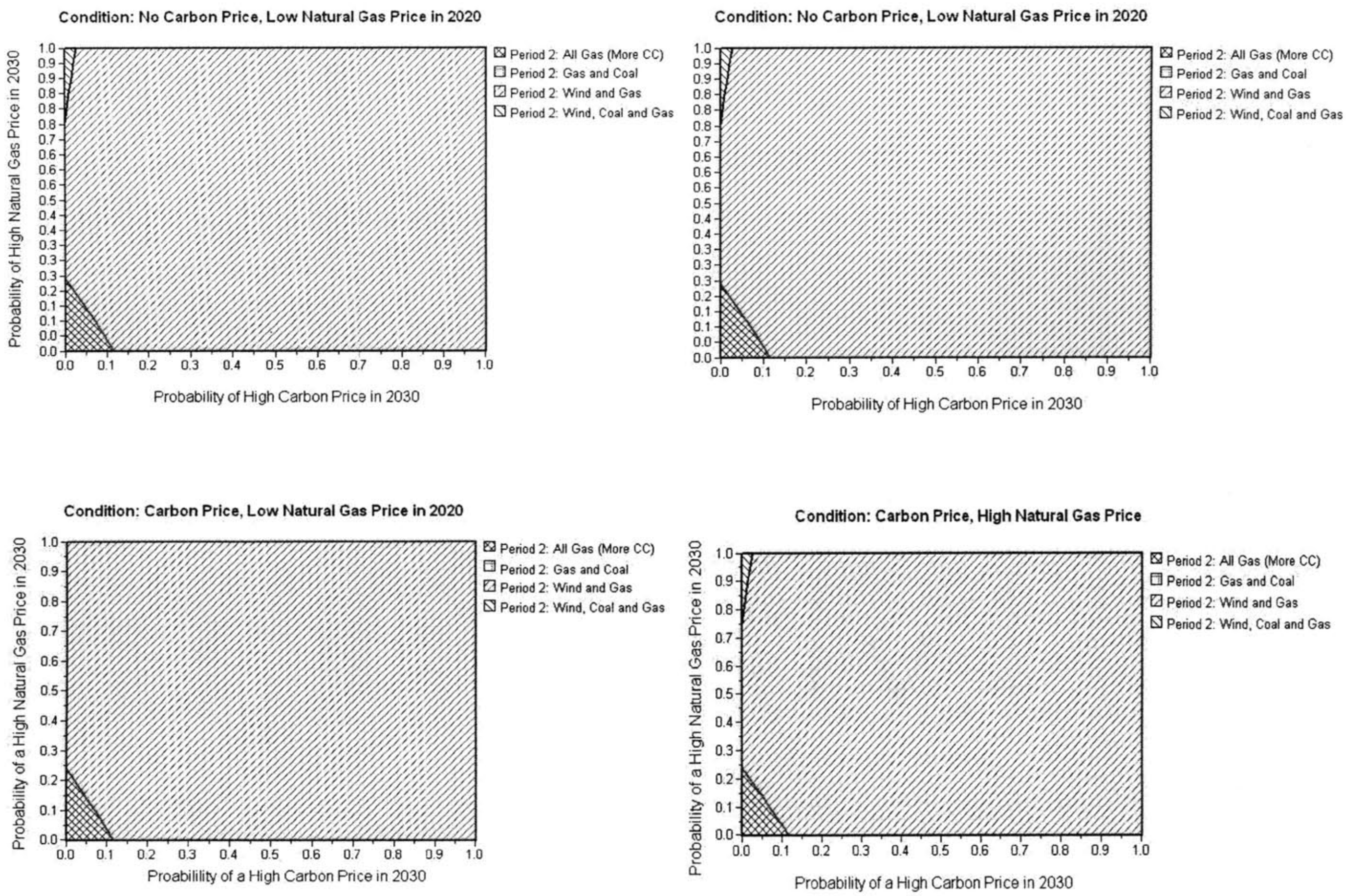

Figure 4.13(a): 2030 decisions given that "All Gas" decision is made in 2020

For all the states, the "Wind and Gas" scenario has the highest probability of being optimal. A low natural gas price combined with a low carbon price leads to the "All Gas" scenario. From Figure 4.13 (a), this is true for all states given that the probability of a high carbon price is below 0.1 and the probability of a high natural gas price is blow 0.25. Also, when there is a high natural gas price, and the probability of a high carbon price is low, the "Coal and Gas" scenario yields the cheapest system costs. This does not hold under the condition that there was a carbon price and a low gas price in 2020. This combination eliminates the coal completely in 2020 as shown in 4.3.3.1.

Condition 2: "Wind, Coal, and Gas" Scenario

The sensitivity analysis here assumes that in 2020, the "Wind, Gas, and Coal" scenario was decided on. Results are shown in 4.13(b).

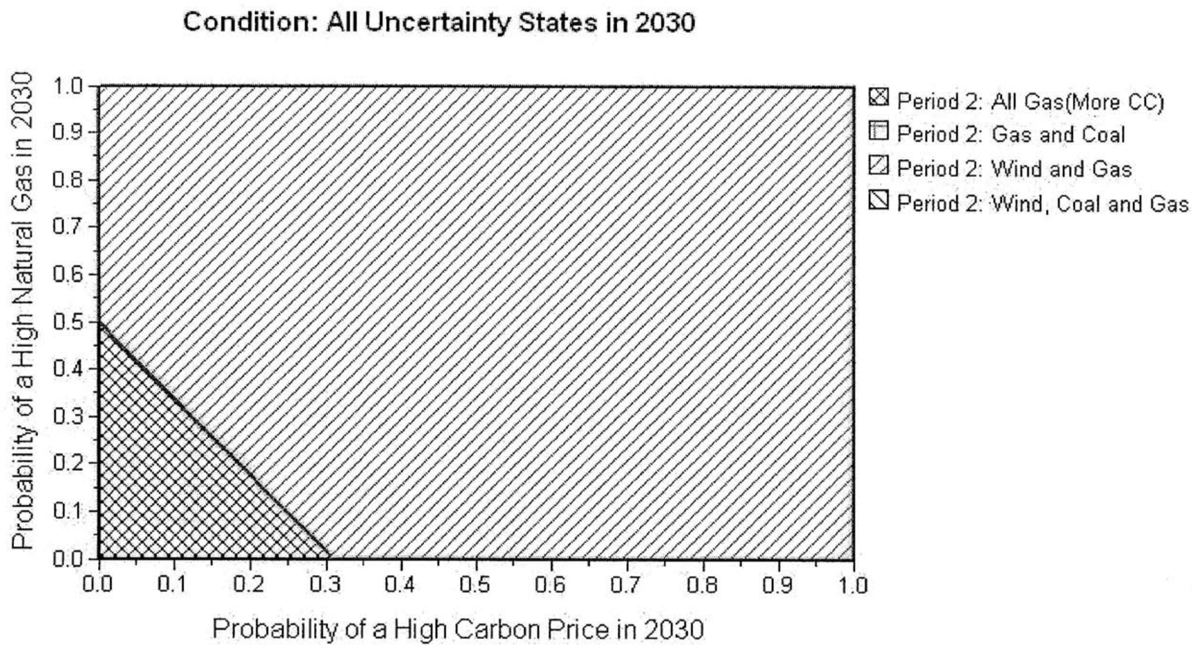

Figure 4.13(b): 2030 decisions given that "Gas, Coal, Wind" decision is made in 2020

For all the states a probability of a high natural gas of 0.5 and lower leads to the "All Gas" scenario given that probability of a high carbon price in 2030 is 0.3 and less. As the high natural gas probability decreases, the "All Gas" is cheaper. Though there is gas in either of the scenarios, in this region, the "All Gas" price is cheaper because of lower capital costs. From the model, the cost of running the "Wind and Gas" scenario are lower than those for running the "All Gas" scenario, however the capital costs make the "All Gas" cheaper in this region.

Condition 2: "Coal and Gas" Scenario

The results in this section assume that in 2020, the "Coal and Gas" scenario was implemented. Figure 4.13(c) summarizes the results of the sensitivity analysis.

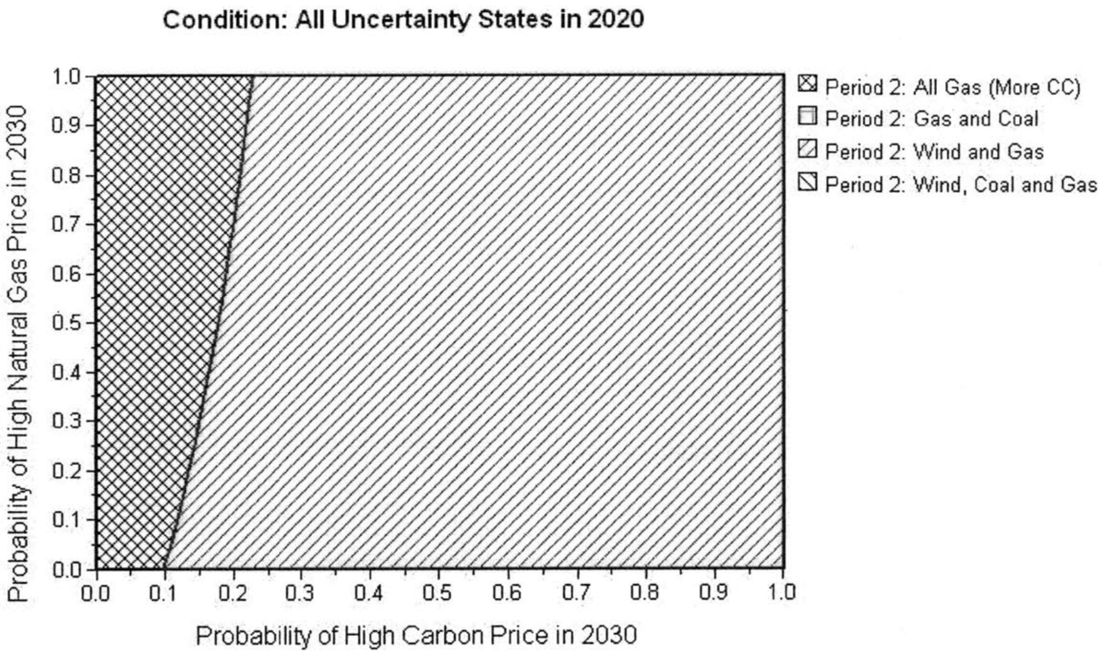

Figure 4.13(c): 2030 decisions given that "Coal Gas" decision is made in 2020

The probability of a high carbon price is dominant. For a probability of a high carbon price of 0.1, regardless of the natural gas price, the "All Gas" scenario is dominant. As the probability of a high carbon price continues to increase beyond 0.1, both the natural gas price and the carbon price affect the optimal choice. As the probability of a high natural gas increases with the likelihood of a high carbon price the "Wind and Gas" scenario becomes cheaper. For low gas price reduces the costs for the "Wind and Gas" scenario faster than it does for the "All Gas" scenario. A high natural gas price favors the "All Gas". Again this is because of the higher capital costs of the "Wind and Gas" scenario.

4.3.4 Technology Evolution

From the results in the decision tree shown in section 4.3.2, the optimal solution in 2020 is the "All Gas" scenario. The optimal solution for the second period is the "Wind and Gas" scenario.

4.3.4.1 Generation Portfolio Evolution (2010 -2020)

In this section, I compare the snapshot of fuel types in ERCOT in 2010 as shown in Chapter 1 and the results of the decision analysis. Figure 4.14 compares the generation fuel types for 2010 and 2020.

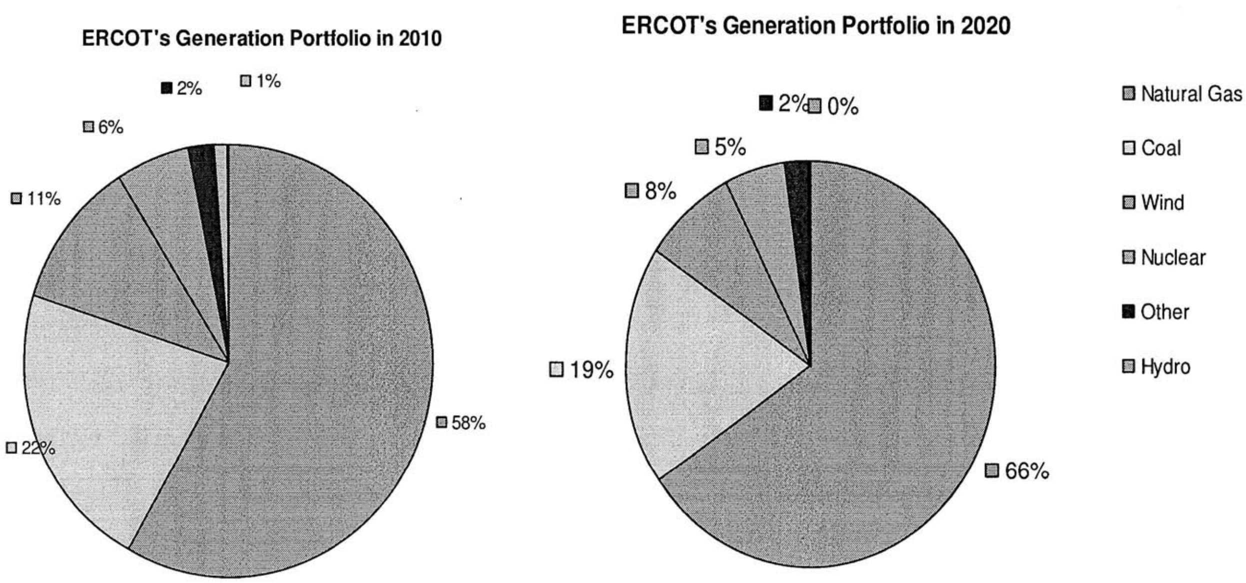

Figure 4.14: Evolution of Technologies between 2010 and 2020

From figure 4.14, there is an 8% increase in natural gas, and a 3% decrease in coal. The amount of wind and nuclear also decreases as a fraction of the total capacity in the system. The amount of hydro in the system is wiped out because of the age of the plants.

4.3.4.2 Portfolio Evolution (2010 -2020)

In this section, I compare the fuel types in ERCOT in 2030 on the condition that the generation evolves as shown in 4.3.4.1. The optimal solution for the second period is the "Wind and Gas" scenario. Figure 4.15 shows the compositions of the resulting when this scenario is assumed.

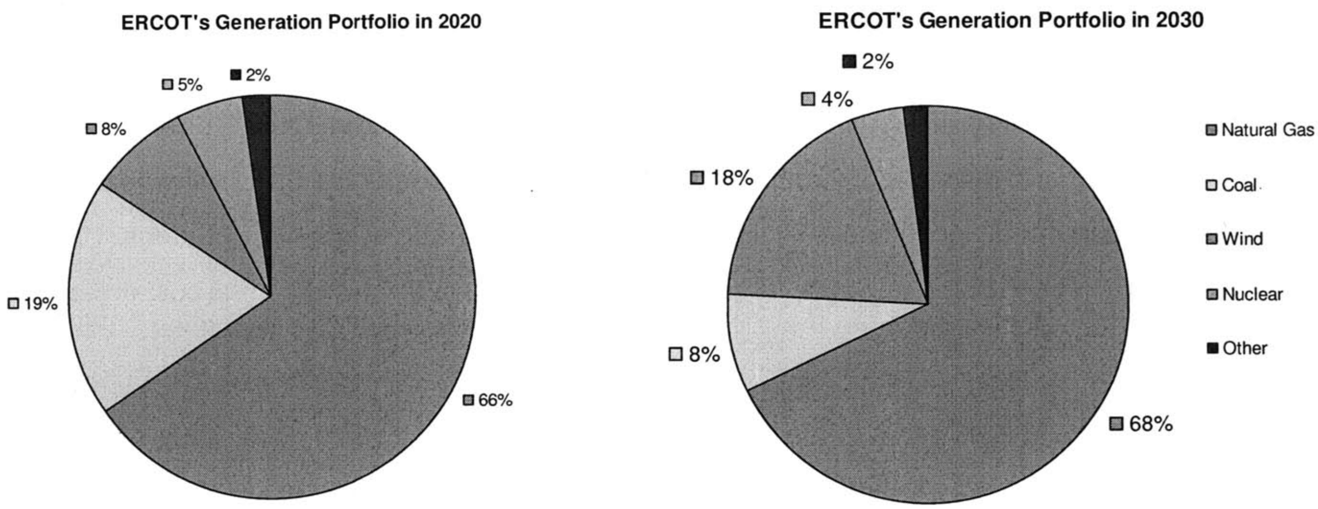

Figure 4.15: Evolution of Technologies between 2020 and 2030 (1)

4.4 Chapter Summary

In this chapter, I analyze the results first assuming that there will be carbon capture and storage technologies available after 2020. Considering CCS, the optimal solution in the first period using the VARG curves and the decision tree is the "All Gas" scenario. In the second period, the "Gas and Coal" with capture is optimal. From 2010 to 2030, percentages of both natural gas and coal increase if this path is taken. Under the conditions, wind development is not competitive.

In the second analysis, with no CCS, the results are more probabilistic. From the VARG curves, the "Coal and Gas" scenario is the optimal solution as it avoids the most risk and also captures the highest gains as the cheapest possible scenario. Results from the decision tree show that the "All Gas" and the "Wind and Gas" scenarios are the optimal solutions in the first and second periods respectively. The sensitivity analysis performed by varying the probabilities in the decision tree, provides a more comprehensive summary of results. At different probabilities of both the natural gas price and the carbon price, there are different optimal solutions. Using the results from the decision tree, natural gas and wind increase in the system while coal decreases.

5.0 DISCUSSION

In this chapter, I discuss the implications of the results presented in Chapter 4 and other factors which may influence the evolution path of generation technology. The results from Chapter 4 are from a purely economic analysis, but this chapter aims to bring in the engineering, political and social considerations that too play a part in this decision making. While the results in the previous chapter are based on ERCOT, the presentation of these results goes beyond the case study. In my presentation of the main findings, I also present the various interests of different stakeholders. I also discuss some limitations in this study.

5.1 Discussion of Results

The analysis done provides insight on the risks in investment in generation technologies. From the various analyses conducted in Chapter 4, the following main deductions were made:

1. The path of capacity expansion taken today depends on the technologies we assume to be available in the future.
2. Unless a price on carbon is established and is high enough, coal will remain competitive.
3. CCS allows for coal to remain an attractive investment in the presence of a carbon price.
4. Wind is competitive when the prices of both natural gas and carbon are high, and in the absence of CCS technologies.
5. Investment in natural gas presents relatively the least risk.

Below, I discuss each of the main themes from the study.

The path of capacity expansion taken today depends on the technologies we assume to be available in the future.

From the results in Chapter 4, perhaps the most interesting deduction is that the decision we make today depends on the technologies that we foresee in the future. This shows the benefit of path dependent decision making. It is therefore important that technology change be considered in capacity expansion models if the optimal decision under uncertainty is to be determined more accurately today.

The role of technology change in the future is important in policy making since policies may be uninformed by this potential and assume only technologies in the status quo. This exemplifies the need to fund R&D of breakthrough technologies such as CCS or ocean-wave energy. Since the emissions challenge is a global problem, there is always a question of where these funds for R&D should emanate from. According to Mancur Olson, parties are unlikely to accept the role of the funder in cases where the costs are concentrated while the benefits are diffuse in this case across the globe (Olson, 1971). I believe that both the private sector and the government have a role to play. For manufactures or technology, there is great potential that new technologies will be timely and capture any carbon policies that may be set. The government may also direct more R&D funds to energy.

Alternatively, establishing a policy on carbon will induce innovation and lead to technology change; improvements to current technologies or new inventions. The establishment of a carbon price therefore plays an important role in technology change and our decision of what to build today.

Unless a price on carbon is established and is high enough, coal will remain competitive. CCS allows for coal to remain an attractive investment in the presence of a carbon price.

In the analysis conducted in Chapter 4, if the natural gas price is high and a carbon price is not established, coal will remain a major component of the technology portfolio in the next ten years unless CCS technologies become available. Moreover, the price that will be placed on carbon should be high enough for other technologies to be competitive. According to Kip Viscusi, an externality exists when the actions of one agent affects the utility of another leading to an inefficient allocation of resources (Viscussi et al, 2005). Carbon emissions are large component of greenhouse gases that are causing global warming and climate change. If the goal is to reduce the impact of this externality, then it is crucial that a carbon price be established in the next ten years to lower emission.

For many systems which currently have coal as the major fuel source, old retiring plants will be replaced with new coal plants and unless CCS technologies are established, the power sector will continue to produce high emissions for longer. CCS technologies are essential if the emissions from coal are to be reduced as echoed by the MIT Study on the Future of Coal and also the IPCC Third Assessment Report. Moreover, the costs of this technology have to be competitive if investors are to willingly purchase it. To be competitive of course, a carbon price has to be established and also it has to be high enough unless command and control policy mechanisms are put in place. This poses another debate- should carbon emissions be regulated like air pollution where such mechanisms are employed? If capture technology is mandated, then this ceases to be an investment question as all utilities would have to comply. However, this form of mechanism is unlikely since more market based solutions are currently being considered such as taxing and cap-and trade.

Another consideration is that there are numerous economies that currently depend on coal as a source of income. Politicians from such economies, commonly referred to as 'brown states', are likely to oppose a price on carbon. According to an article in the New York Times, politicians from mid-west states which rely heavily on coal and manufacturing are in the forefront for opposing any legislature on climate policy with regards to carbon (Broder, 2009). This divide in interests from a socio-economic perspective plays a role in establishment of a carbon price which is crucial to the reduction in climate change. Only if CCS technologies are available at a competitive price can there be resolve between climate change advocates and such economies.

Wind is competitive when the price of both natural gas and carbon are high, and in the absence of CCS technologies.

From the analysis in Chapter 4, in the first ten years, wind is only a part of the optimal portfolio when there is a high natural gas price and a high carbon price. This is a favorable circumstance for wind investors and also manufacturers of wind turbines. In the second stage, when a carbon price has been established for certain, wind becomes a consistent component of the optimal solution assuming that CCS technologies have not been established.

There are numerous reasons why the diffusion of wind and other renewables is currently attractive to most governments. In addition to reducing climate change, renewables promise energy sustainability and security, and economic boosts for communities with resources. Wind that has currently been built especially in Texas, which is currently the leading US wind producer, was mostly spurred by the state adopting Renewable Portfolio Standards (RPS). RPS essentially is the government picking a technology. If instead a carbon price is established, then the market will be able to develop wind without the need for government intervention.

Again, this is another question of which mechanisms work best here- market or policy. To most economists, the market based solutions are most effective for market problems (Viscussi, 2005). If a market solution is to be employed, then the carbon price is essential to expansion of wind. If instead, the command and control approach is taken, there is risk of regulatory capture as that which occurred in Texas in the late '90s. Regulatory or Stiglerian capture is institutional failure in which, companies' self interests coincide with the interests of the regulation setting body (Oye et al, 1994). Enron lobbied the Texas government to mandate RPS and became the supplier of wind turbines to investors in Texas. Such instances are common in regulation and standard setting and these weaken the credibility of policy mechanisms. Moreover, it is imperative that policies be aligned with social needs instead of needs of private organizations.

Another important consideration with wind besides investment is the reliability of electricity systems and grids. Here, I define reliability in terms of both adequacy and security. Inherently, wind like most renewables requires operational reserves to be available in the system to balance its variability and intermittency. As a result, investment in wind should be coupled with a more reliable technology. Currently, fossil fuels are used. However, other fuels such as nuclear energy should be used considered if the goal is to achieve a lower carbon economy.

Investment in natural gas presents relatively the least risk.

From the results in Chapter 4, natural gas will play an important role in the next twenty years whether it s priced high or low. Building purely natural gas plants from here on forward may lead to the lowest costs in the system with the most reliability. In the US, recoverable shale gas reserves have put confidence that there is enough natural gas for centuries to come (Petak et al, 2009). The abundance of the resource makes it a viable alternative to coal. Natural gas has lesser carbon emissions than coal and in numerous studies it has been seen as a bridge to a lower carbon economy. This finding of unconventional natural gas sources which has been referred to as a 'game changer' also implies that natural gas prices may not increase in the margins that current forecasts assume. In this case, natural gas investment will increase as the resource becomes cheaper even without a carbon price.

In as much as natural gas offers the benefits of a lower carbon economy, it is debatable whether this is enough to lead us to desirable CO_2 stabilization levels. While it is a solution in the short term, other technologies should be considered to lower the power sectors carbonemissions.Taking natural gas as the bridge to a lower carbon economy essentially locks in investors to one fuel source. When will the bridge be crossed if natural gas continues to be a major part of the generation portfolio? The potential increase in natural gas investment threatens government goals to diversify their energy portfolios. Besides that we await some breakthrough technologies, there are other fuels such as nuclear energy. Lock-in has the potential to inhibit

R&D efforts to either develop new technologies or to fund studies that may gain public confidence in the use of nuclear energy for example.

Natural gas from the results in this study is the most economical fuel given the options that we currently have. However, it presents a risk of reducing the diversity of technology portfolios and also the continued reduction of carbon emissions. Policy instruments may need to intervene to direct investment to other fuel sources to avoid reliance on a single energy source.

5.2 Limitations of the Study

The aim of this thesis is to develop a strategy that may protect investors from the risk that is presented by the uncertainties that are currently characteristic of the energy industry. The method used in developing this strategy while more detailed than traditionally used model also has some limitations. There are limitations in the assumptions of scope and also in the tools available to address the problem.

In terms of the scope, in recent years it is important to think about electricity from both the generation side and the demand side. This thesis assumes that there is a constant growth in demand and that all new demand is met purely from the generation side. It is however, important to understand that there are numerous demand side initiatives that lower the amount of new capacity that is needed such as distributed generation. Large scale solar systems for example are cheaper on a distributed generation level. Also, there are numerous energy efficiency programs that are currently underway and will reduce the amount of energy that is needed in the future.

Another assumption in the scope is that only three fuels are available for investment through out the next twenty years. The current energy climate has spurred a lot of investment in research and development for new technologies and ways to improve the existing technologies. For this study, it would be useful to add the uncertainty in the availability of CCS to the uncertain carbon and natural gas prices. Besides CCS, there are other technologies that may change the parameters that were used in this thesis. Moreover, in the extreme case, disruptive technologies may enter the market.

Finally, in running simulations in PowerWorld a number of simplifications were made. In particular, transmission line constraints were disabled. As a result, some generators that may in fact have insufficient transmission were allowed to be dispatched. Also, to maintain reliability in the system, security constrained optimal power flow (SCOPF) should be used instead. SCOPF checks that in spite of any possible disturbances in the system, there is a contingency to make sure that demand is served.

5.3 Chapter Summary

The results obtained in Chapter 4 show that natural gas as an investment presents the least risk. While this is favorable in the short term, as natural gas has lower carbon emissions than coal, it presents long term risks of reducing fuel diversity and further emissions reductions. There may be a need for policy instruments to direct investment to other fuels to fulfill government goals of energy sustainability and security for instance. Coal remains a possible investment option and the prospect of CCS technologies is favorable to coal mining economies. Wind becomes competitive given that there is a high carbon price established and also that natural gas prices are high, assuming that CCS technologies are not brought to the market. Without this condition, policy instruments like RPS will have to be implemented or continued to support its diffusion.

6.0 CONCLUSIONS

In this thesis, the aim was to develop a strategy for investment in power generation technologies in the future given the uncertainties in climate policy and fuel prices. The electricity sector produces 40% of carbon emissions, and any climate policy will heavily impact the sector. These uncertainties change the cost structure of technologies as we currently know them, and this poses risk to investors in power generation. As demand continues to grow, new investment is required and therefore a strategy to invest under such conditions is necessary. This thesis examines the way that technology portfolios are likely to evolve in light of these uncertainties.

Capacity expansion in the long term commonly conducted uses deterministic methods. Deterministic approaches determine solutions given exact parameters with no room for variation in the likelihood of different scenarios. In this study, use a probabilistic approach which explores given scenarios under assuming varying likelihood. In addition, capacity expansion models conventionally use average estimates to predict the amount of power that each generator will produce based on the technology. In this thesis, I propose an alternate method which determines the actual generation of a unit in a system hour-by-hour. This is motivated by the intermittency and variability of wind generation. The hypothesis is that by so doing, a more accurate representation of system costs is made.

I used the Electric Reliability Council of Texas (ERCOT) as a case study and investigated the effect on system cots of different types of generation technology investments over a period of twenty years. Using a dispatch model, I simulated a sample of hours of the load duration curves for 2020 and 2030 assuming different demand levels. In the first period 2010-2020, I assumed the price of carbon to either be \$0 or \$50/ton CO_2. In the second period, I take the carbon price to be at either a low of \$25/ton of CO_2 or a high of \$100/ton of CO_2. The price of natural gas used was either a high of \$15/MMBtu or a low of \$3/MMBtu in both periods. Each of these hours had a different amount of wind generation from sampling Weibull distributions of historical patterns in wind generation based on the season and the time of day. I simulated each technology scenarios for the four uncertainty combinations. Each of these scenarios was simulated three times to capture different wind levels. The average of these three scenarios was the system output. The output was the system costs for each our aggregated over a year. I assumed a 5% discount rate to calculate the present value of cost of running the system. The results from each of the simulation were then evaluated in a decision tree to establish the socially optimal solution.

I the present the results in different visualization styles: VARG curves, sensitivity analysis and decision tree with a 0.5 probability for all the uncertainties. From the VARG curves the investment portfolio that avoided the most risk and also had the lowest possible costs was the "Coal and Gas" scenario. From the sensitivity analysis, the optimal solution depended on the probabilities assumed. In the first stage, the "All Gas" scenario was the most prevalent. In the second state both the "Wind and Gas" and the "All Gas" scenario are most likely. From the decision tree, I found that in the first period (2010-2020) building all natural gas plants is the optimal solution. In the second period (2020-2030), the optimal solution is a combination of wind and natural gas.

To stir investment paths suggested by this thesis, a carbon price plays an essential role. A carbon price will give lead to both CCS technologies and renewables such as wind becoming competitive with the fossil fuels. Natural gas is also an important component of the technology mix and will continue to do so unless capture technologies becomes prevalent soon and also other fuel alternatives are explored.

Future Work

To further the foundation laid by this thesis, I propose that the following work be done.

1. Expand the study to other technologies such as nuclear and other renewables. Only wind, coal, and gas are considered in this study, other technologies could be included in the studies scenarios that were tested.

2. Include pricing of other greenhouse gases as uncertain in the future. These gas include NO_x and SO_2

3. Analyze other uncertainties such as technology change and electricity demand. In particular, it would be useful to add the uncertainty in the availability of CCS technologies.Technology change is essential to avoid risk in betting on technologies whose development or feasibility is uncertain. Varying demand levels takes care of the uncertainties in demand and also demand-side management.

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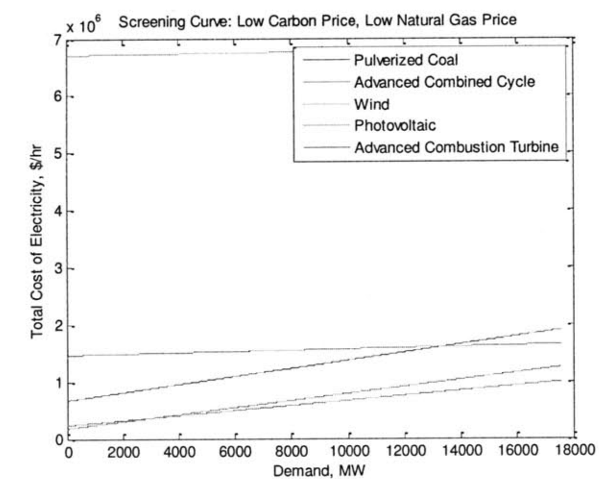
APPENDICES

Appendix 1: Screening Curves

The following figures and tables show the screening curves that were developed to allocate generation capacity across the different technologies. I present the scenarios in 2020 and then for 2030. Accompanied with each curve are the capital costs for the resulting technology mix outlined in a table.

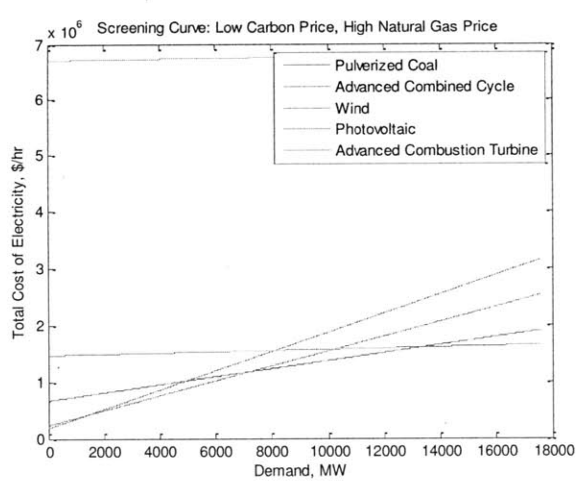
1.1 Screening Curves for 2020

1. Low Carbon Price, Low Natural Gas Price



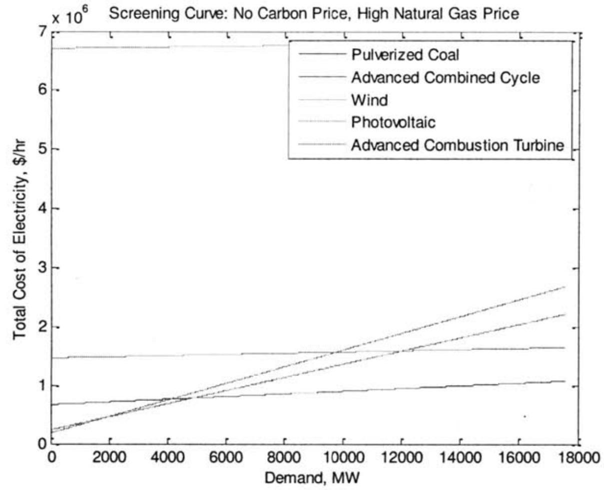
	Cost/MW	Gen	Total Cost
PV Coal	2650000	0	0
ACC	880000	14572	12823360000
Wind	2350000	0	0
ACT	650000	3000	1950000000
		Total	-14773360000

2. Low Carbon Price and High Natural Gas Price



	Cost/MW	Gen	Total Cost
PV Coal	2650000	6000	15900000000
ACC	880000	5750	5060000000
Wind	2350000	4322	10156700000
ACT	650000	1500	975000000
		Total	-32091700000

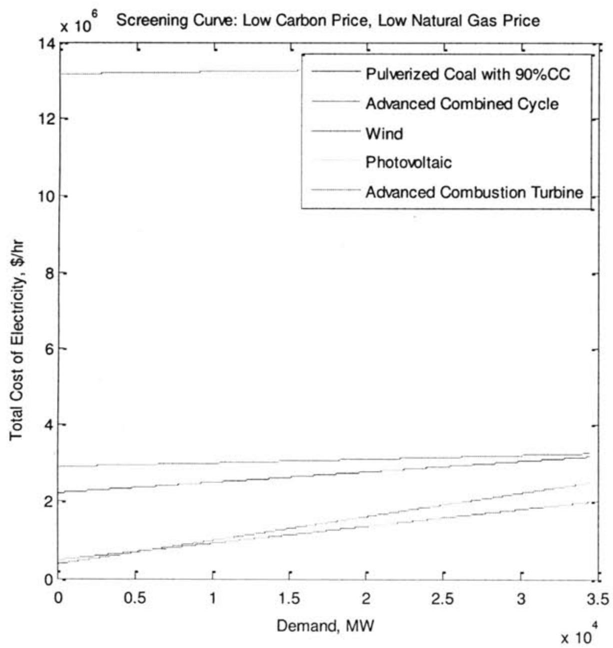
3. No Carbon Price, High Natural Gas Price



	Cost/MW	Gen	Total Cost
PV Coal	2650000	12572	33315800000
ACC	880000	3000	2640000000
Wind	2350000	0	0
ACT	650000	2000	1300000000
		Total	-37255800000

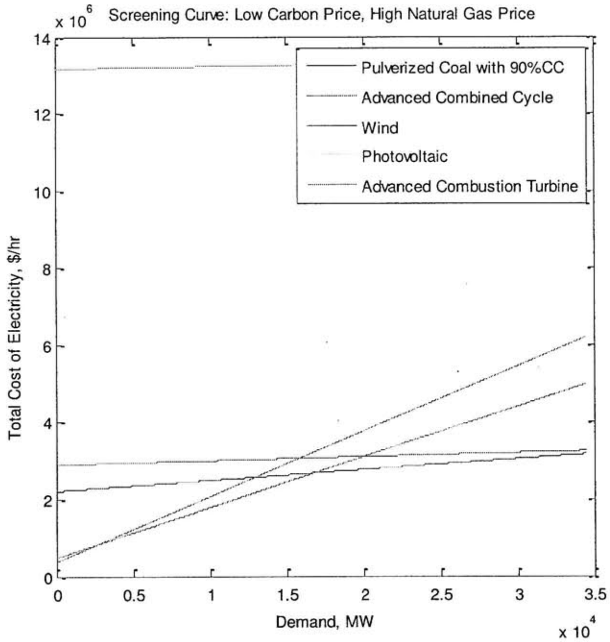
1.2 Screening Curves for 2030

1. Low Carbon Price, Low Natural Gas Price



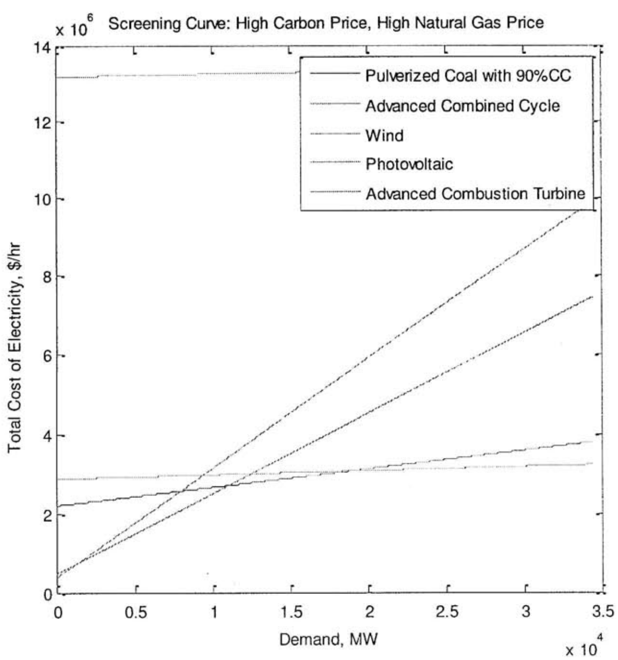
	Cost/MW	Gen	Total Cost
PV Coal w/ CC	4435000	0	0
ACC	902000	12177	10983654000
Wind	2350000	0	0
ACT	675000	2500	1687500000
		Total	-12671154000

2. Low Carbon Price, High Natural Gas Price



	Cost/MW	Gen	Total Cost
PV Coal w/ CC	4435000	7677	34047495000
ACC	902000	5000	4510000000
Wind	2350000	0	0
ACT	675000	2000	1350000000
		Total	-39907495000

3. High Carbon Price, High Natural Gas Price



	Cost/MW	Gen	Total Cost
PV Coal w/ CC	4435000	3000	13305000000
ACC	902000	4500	4059000000
Wind	2350000	6677	15690950000
ACT	675000	500	337500000
		Total	- 33392450000

Appendix 2: Technology Characteristics

Here, I give the prices and values for the various characteristics used in this thesis in the development of scenarios and prices

Price of Coal = \$1.63/MMBtu
NO_x Price = \$2000/ton of NO_x

Table 1 gives the heat rates of the different technologies considered in this thesis.

Table 1: Generator Heat Rates

Technology	Heat Rates (Btu/KWh)
Natural Gas Combined Cycle	7260
Natural Gas Combustion Turbine	9000
Pulverized Coal	9100
Pulverized Coal with 90% Capture	12460

Table 2 gives the CO_2 emissions rates of the different technologies considered in this thesis.

Table 2: Generator CO_2 Emissions Rates

Technology	Emissions Rates(lb/KWh))
Natural Gas Combined Cycle	800
Natural Gas Combustion Turbine	1200
Pulverized Coal	2100
Pulverized Coal with 90% Capture	210

Table 3 gives the NO_x emissions rates of the different technologies considered in this thesis.

Table 3: Generator NO_x Emissions Rates

Technology	Emissions Rates(lb/KWh))
Natural Gas Combined Cycle	0.5
Natural Gas Combustion Turbine	0.7
Pulverized Coal	1
Pulverized Coal with 90% Capture	1

Table 4 gives the sizes of the different technologies considered in this thesis.

Table 4: Size of Generators

Technology	Capacity (MW)
Natural Gas Combined Cycle	400
Natural Gas Combustion Turbine	300
Pulverized Coal	750
Pulverized Coal with 90% Capture	750

Table 5 gives the fixed O&M costs of the different technologies considered in this thesis.

Table 5: Fixed Operation and Maintenance Costs

Technology	O&M Costs ($/MW)
Natural Gas Combined Cycle	1.6
Natural Gas Combustion Turbine	5.1
Pulverized Coal	3.8
Pulverized Coal with 90% Capture	3.8
Wind	10.4