**Technology Investment Decisions under Uncertainty:**
**A New Modeling Framework for the Electric Power Sector**

by

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## ABSTRACT

Effectively balancing existing technology adoption and new technology development is critical for successfully managing carbon dioxide ($CO_2$) emissions from the fossil-dominated electric power generation sector. The long infrastructure lifetimes of power plant investments mean that deployment decisions made today will influence carbon dioxide emissions long into the future. New technology development and R&D decisions can help reduce the overall costs of reducing emissions, but there are multiple technology investments to choose from, and returns to R&D are inherently uncertain. These features of the technology "deployment versus development" question create unique challenges for decision makers charged with managing cumulative carbon dioxide emissions from the electricity sector.

Unfortunately, current quantitative decision support tools ultimately lack one or more of three overarching features jointly necessary to provide useful insights about an optimal balance between R&D program and power plant investments. They lack (1) resolution of the critical structure of the electricity sector, (2) an explicit endogenous representation of the effects of learning-by-searching technological change, and/or (3) an efficient decision-analytic framework to explore multiple technology investment options under uncertainty in the returns to R&D.

This dissertation presents a new quantitative decision support framework that allows for the study of socially optimal R&D and capital investment decisions for the power generation sector. Through a novel integration of classical electricity generation investment planning methods, economic modeling of endogenous R&D-driven technological change, and emerging numerical stochastic optimization techniques, the new framework (1) explicitly accounts for the complementary roles that generating technologies play within the electric power system, (2) considers the characteristics of the uncertainty in the technology innovation process, and (3) identifies flexible, adaptive R&D investment strategies for multiple technologies for decision makers to consider.

A series of numerical experiments with the new model reveal that (1) the optimal near-term R&D investment strategy under technological change uncertainty and adapting between decisions can be different than the optimal strategy assuming perfect foresight,

and may be *higher or lower*; (2) *the timing* that a technology should be deployed to meet a specific carbon target dictates the direction and magnitude of the difference in these decisions; (3) increasing the level of uncertainty tends to increase near-term R&D investments; and (4) increasing right-skewness of the uncertainty (i.e., decreasing the likelihood of higher than average returns), reduces R&D spending throughout the planning horizon.

Thesis Supervisor: Mort D. Webster
Title: Assistant Professor of Engineering Systems

## Acknowledgements

Several people and organizations provided support for this dissertation that I wish to acknowledge. I am profoundly grateful for each of their unique contributions to my research during the past four years.

First and foremost, I would like to thank Mort Webster, my MIT Engineering Systems Division (ESD) PhD program advisor and dissertation committee chair. To simply acknowledge that he has been invaluable to my growth as a researcher, and a person, would be unfair. From the time we met in 2008 when I entered the PhD program—as a relatively inexperienced numerical modeler with a passion to work on electricity planning and policy issues—to now, I have experienced a tremendous transformation. Mort's own passion for his work, enthusiasm for teaching and mentoring, availability and interest in participating in the "mundane" research tasks of computer coding and editing, and uncanny ability to treat his students with the utmost respect and professionalism, while still guiding and correcting, provided an unmatched source of motivation and creativity I imagine other doctoral students only wish for.

I also thank my doctoral dissertation committee, Joseph Sussman, Ignacio Pérez-Arriaga, and David Popp for their guidance and support during the past four years. To state that this particular combination of professors constitutes an "All Star" dissertation committee would also be an understatement. From the perspective of my research, which brings together the fields of electric power system planning, the economics of technological change, and uncertainty and decision analysis to study investment planning under uncertainty in the electric power sector from an engineering systems perspective, I could not have formed a more knowledgeable and supportive committee. I thank each of them for their participation—for the questions asked, comments provided, and overall instrumental contribution to the dissertation work. Finally, I would like to extend a special thank you to Professors Panos Parpas of Imperial College, and Andrés Ramos and Javier García Gonzáles of the Institute for Research in Technology at Comillas University, for their assistance in constructing and reviewing the electricity planning model and stochastic optimization algorithms used in the dissertation. I also thank the Institute for Research in Technology for graciously hosting my research in Madrid during the summer of 2011.

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This dissertation is dedicated to the two people in the world who deserve more credit for this document and all the work that went into it than me—my husband, Sean, and our baby due in mid-November. Sean, for being more than just my rock, but what would more aptly be described as my life support. Through countless packed lunches, made dinners, late night campus pick-ups, clean laundry, and last-minute proofread pages, he always remained thoughtful and available as a listening ear and neck-massaging hand. And, our soon-to-be-born little baby, for somehow bestowing upon me a new courage to find the exact amount of energy and drive I needed to overcome the final hurdles in my dissertation marathon before she was born.

Nidhi Rana Santen
Cambridge, Massachusetts
October 2012

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# Chapter 1 Introduction

Effectively managing carbon dioxide ($CO_2$) emissions from fossil-based electric power generation is critical for executing a comprehensive global climate change mitigation and risk management plan. In the United States, for example, the electric power generation sector is responsible for approximately forty percent of the country's annual emissions (Energy Information Administration, 2011). Unfortunately, many of the technologies for significantly reducing $CO_2$ emissions from the electricity sector are either in early conceptual stages or available at relatively high costs or small scales, requiring additional research and development (R&D). Meanwhile, the industry continues to meet increasing electricity demands with carbon-emitting technologies that are both commercially available and economically viable. This pattern repeats itself throughout the industrialized world, and more troublingly, intensifies across the industrializing world where electricity demand and fossil-based generation are expected to track near-exponential rates of economic growth.

To address the dilemma of resolving increasing electricity demands with emission reduction goals, policy makers are interested in the dual role that environmental policy instruments can play in near-term carbon reductions by incentivizing existing low-carbon technology adoption, and in long-term carbon reductions by incentivizing private R&D. Likewise, the possibility that early and direct public investment in R&D can reduce the overall cost of mitigating future climate damages is attractive to many stakeholders. However, identifying the best policies remains elusive due to the complexity with which different policy instruments induce existing technology deployment versus new technology R&D; the magnitude of uncertainties associated with the outcomes to R&D; and the long lifetimes of electric power capacity investments. Figure 1-1 conceptually summarizes policy-induced technological change and the complex interactions that exist within the power generation sector, many of which are studied in this dissertation.

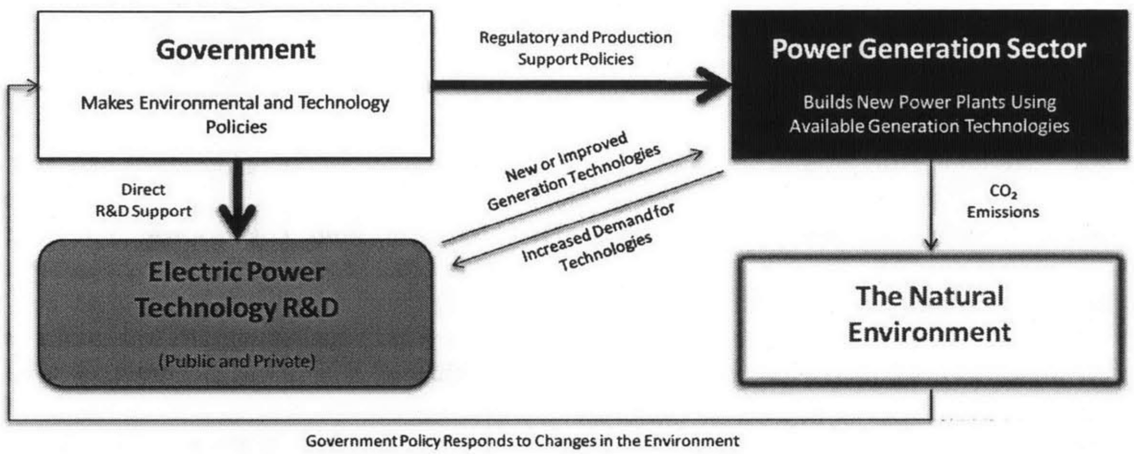


**Figure 1-1 Policy-induced technological change in the electric power generation sector**

## 1.1 The Problem

Electric power generation plants require massive investments and have very long infrastructure lifetimes. It is not uncommon for a new large state-of-the-art coal-fired power plant to cost almost $4 billion to build, while a single new moderately-sized offshore wind farm to cost well over $2 billion (Energy Information Administration, 2011)[1]. Moreover, several of these investments will continue to operate and emit carbon dioxide for at least fifty years, some closer to sixty or seventy years into the future. The decisions made today regarding how to best meet growing electricity demand and how to

[1] Capital cost estimates are derived from a state of the art dual-unit 1200 MW IGCC plant and a 400 MW offshore wind farm, respectively.

attain specific objectives such as carbon emissions reduction in the near term (e.g., for the next five years) are therefore de facto decisions about meeting electricity demand and achieving other objectives long into the future.

This decision making faces several immense challenges in the context of meeting new environmental objectives and investing public (or private) monies in R&D programs. First, it is unclear how policy decisions made on the sector's behalf (e.g., a carbon cap) or specific R&D investment decisions will ultimately affect actual carbon emission reductions and costs in such a unique sector. Although infrastructure costs, lifetimes, and other characteristics of the electric power system match other large-scale infrastructure-heavy systems, a facet that sets it apart is the necessary interaction between highly complex, time-dependent technical operations and the infrastructure itself. This feature requires a diverse portfolio of technologies during any given period of time in the system working together seamlessly to balance each other over very short time-scales (e.g., fractions of a second to minutes) to deliver reliable electricity. Unfortunately, their long lifetimes and capital intensive nature mean that these same technologies will also continue to operate in the system for decades after they are built, influencing long-term environmental goals. These complex policy-operations interactions are only beginning to be understood in the policy realm, and are thus not yet well represented in decision support tools (e.g., numerical models) for those actually making policy and funding decisions. However, as there is great interest in meeting objectives at least cost, it clearly becomes important to consider the effect that activities such as R&D (pursued with the express intention of reducing costs) can have on the evolution of the system.

Adding to this challenge are the multitude of uncertainties decision makers face in having to make investment decisions today that will continue to affect operations and other investment choices well into the future. In the context of R&D decision making, one of the greatest uncertainties rests in the outcomes of R&D efforts. The innovation and R&D process is inherently uncertain and thus best described by a probability distribution of outcomes to specified levels of R&D effort (e.g., dollars of R&D invested) (Mansfield, 1968; Evenson & Kislev, 1975). Moreover, these probability distributions are often highly skewed. The majority of outcomes are smaller, more incremental, and less individually valuable contributions to overall technological change, with few occurrences of high value, breakthrough-type innovations (Jaffe & Trajtenberg, 2002; Pakes, 1986). Figure 1-2 schematically depicts the characteristically skewed distributions for outcomes to R&D effort. Additionally, the shape of these distributions can be quite different for different technology groups within the same industry. Though still skewed, distribution profiles characterizing technologies that seem to experience "slow and steady progress," across different levels of R&D co-exist with profiles for technologies that fall into a more "high-risk, high-reward" type of innovation process (Chapter 6).

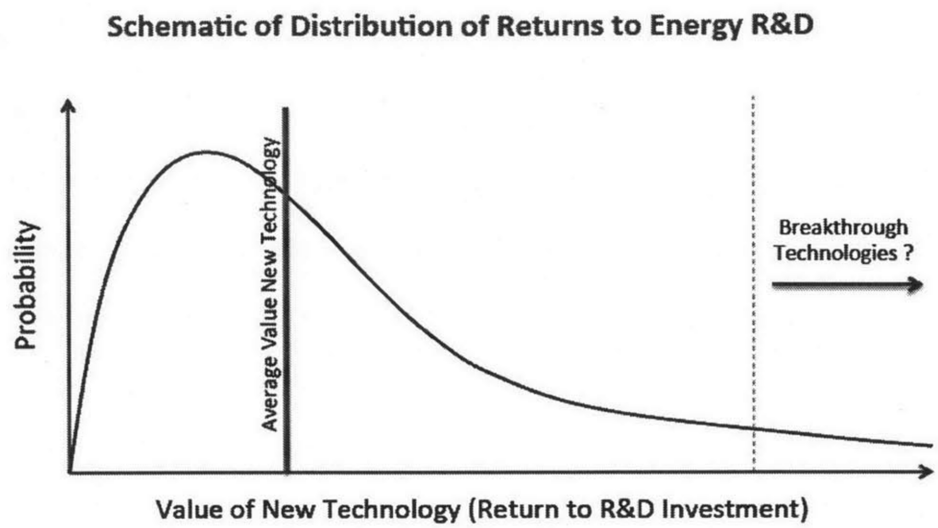


**Figure 1-2 Characteristic skewed distribution of returns (outcomes) to R&D investments**

Unfortunately, considering this uncertainty and the spectrum of possible outcomes to R&D investment within the context of energy decision and policy analysis models is rare in practice; it is even less common in decision models that include details about electric power sector evolution in response to changes in policy and R&D decisions. When combined with the already challenging problem of resolving the effect of (static) policy and R&D activities on operations and optimal generation planning in the electric power sector described above, it is not surprising that uncertainty and differences in risk profiles across different technologies have not yet become integrated into decision support models.

Finally, modern decision support models for investment planning within the electric power sector are not currently structured to match the manner in which policy makers and other stakeholders actually make decisions. Decisions about long-term problems, such as how best to develop the electric power sector to manage climate concerns, are necessarily strategic and rely on concepts of adaptive management. Decisions are made at different time intervals, between which additional information about the state of the world (e.g., actual technology evolution, current exogenous policies) and outcomes of past decisions are collected and assessed. For example, private companies and electric utilities do not choose one R&D plan or capital deployment plan at one point in time and then necessarily stick to that plan for long time periods. They make the best decision they can with information they have available and then wait for additional information to arrive before making a next "best" decision. Such a strategy is particularly important in the highly capital-intensive electric power generation industry, with power plant investment (deployment) decisions being relatively "irreversible." Similarly, policy makers do not obey a single-path decision rule; set "check points" are built in to most environmental and other laws to assess the effect of past decisions and decide whether adjustments to the original plan are warranted to best meet the overall objective. Unfortunately, current decision support models in this area are structured assuming that decision makers do stick to a single path throughout time. In the context of R&D and "irreversible" capital investment planning, these models do not appropriately consider the inherent stochasticity in technological change or the desire for stakeholders to revise and update their decisions over time.

## 1.2 Purpose of this Dissertation

The purpose of this dissertation is to present a new decision support framework that addresses the interplay and challenges discussed above and allows for rigorous study of socially optimal parallel R&D and capital investment decisions for the electric power generation sector. The new framework considers the complementary roles that generating technologies play within the electric power system, the physical integration constraints they face, and the economics at play in electric utilities' least-cost investment decisions, given the economics of technological change. The new framework also overcomes challenges in considering uncertainty and the characteristics of the uncertainty surrounding the energy innovation process itself, as well as the need for decision makers to adaptively manage their decisions to new information over time. Together, these components have important implications for what drives technology adoption and development, and thus emissions reduction, in this unique sector. Results obtained from the decision support model can provide insight and information to the policy process for the electric power sector, and the numerical modeling framework itself is intended as a springboard for further model development and future analyses in this area.

## 1.3 Framing the Research Questions

The modeling framework introduced in this dissertation seeks to provide decision makers with insight about how to optimally balance near-term efforts to reduce emissions from the power sector with future efforts. Specifically, the numerical model is capable of studying socially optimal balances of intra-temporal and inter-temporal capital investments and technology-specific R&D expenditures for the U.S. electricity generation sector.

A simple framing of the specific problem studied is as follows: if the overall goal is to limit cumulative emissions from the power sector by a certain amount (or reach a set emissions target by a certain future date) while continuing to meet demand reliably and efficiently, and there are two pathways for achieving this—1) direct emission cuts (e.g., through constraining regulations and market-based incentives) that force or incentivize currently available (but possibly expensive) clean-technology deployment downstream at the electric utilities, and 2) indirect emission cuts through R&D investment that can make currently expensive technologies cost-competitive with their "dirtier" counterparts at some point in the future—what is the most cost-effective method for allocating these two efforts through time? The question can be framed as one about "now versus later," as well as about "deployment versus development"—how much effort or money do we expend to push deployment of currently expensive technologies capable of reducing emissions and meeting demand now, versus how much do we expend to drive innovation and R&D capable of reducing emissions and meeting demand later?

When uncertainty is explicitly considered these questions become fundamental ones of risk management and hedging against future costs, turning to concepts of portfolio optimization under uncertainty. How do we optimally allocate our efforts between the two pathways in the near-term, cognizant of the fact that we cannot predict the future of technological change and cost paths for different technologies, but knowing that we can learn about outcomes to R&D as they unfold, and update our future decisions accordingly?

The new modeling framework is presented using the U.S. electric power sector as a case, although it can be adapted to power systems in other nations with relative ease. The model is also presented from the perspective of $CO_2$-reduction and climate change policy, but it can likewise also be used to study other environmental policies when applied to other "stock-type" environmental pollutants for which emission reduction targets exist and a multi-year reduction plan may be suitable.

The new modeling framework in this dissertation is motivated by the following three research questions:

(1) What is the optimal intra- and inter-temporal balance between electricity generation capital investments and R&D investments under technological change uncertainty?
(2) How does the optimal investment strategy under uncertainty compare to the deterministic investment strategy design?
(3) What role do R&D program risk profiles and specific electricity generation technology characteristics have in investment planning under uncertainty for the power sector?

## 1.4 Dissertation Structure

This dissertation comprises three main sections: a background and overview of the system and literature review; a description and demonstration of the new modeling framework under static (deterministic) planning; and a description and demonstration of the full new stochastic modeling framework applying approximate dynamic programming techniques for sequential decision making under uncertainty. Below, each chapter in the dissertation is listed and introduced briefly.

To provide background and context for the current work, Chapter 2 presents an overview of the U.S. electric power sector and the U.S. energy innovation system. Details about the unique structure of the industry are included, and the focus of the section is on the generation sub-sector. The section on the U.S. energy innovation system provides an overview of the pathways for innovation that exist for the energy (and electricity) industry, the entities engaged in the innovation process, and a review of recent R&D spending and its effects in the power sector.

Chapter 3 provides a review of the literature on the three main academic areas this dissertation fuses—electricity generation sector investment planning, technological change within energy decision models, and methods for decision making under uncertainty. The section on generation sector investment planning provides a brief overview of the main methods used for investment planning and study. In the sections on technological change in energy decision models and methods for decision making under uncertainty, the focus is on presenting recent studies that define the current state of the art in energy and electricity R&D and capital investment planning models, and integration of uncertainty analysis within these models.

Chapter 4 introduces the numerical modeling framework developed and used for the deterministic study on optimal electricity generation technology R&D and capital investment strategies under endogenous "learning-by-doing" and "learning-by-searching" technological change. The structure of the problem is presented, followed by details about the model's mathematical formulation, integration of technological change dynamics, data, and solution approach. Results from the reference model are presented.

The goal of Chapter 5 is to demonstrate the new modeling framework's capabilities and to motivate the need for further uncertainty analysis. Six numerical experiments are performed to gain insight about behaviors of key variables and the optimal investment strategy under different conditions. First, optimal R&D and capital investment strategies are explored over a range of different cumulative carbon emission targets. The next three experiments study behaviors of the optimal investment strategy across different learning pathways and technology-specific differences in the innovation process. The fifth experiment explores the case of solar power technology in more detail. Finally, the sixth experiment presents results from testing a status quo U.S. energy policy in the modeling framework. The chapter closes with a summary and recounts the key insights gained from each of the experiments.

Chapter 6 introduces the stochastic modeling framework used for the sequential decision under uncertainty model. The full structure of the model and its components are presented, including the characterization of uncertainty in R&D outcomes. The approximate dynamic programming algorithm developed to numerically solve for the optimal investment strategies under uncertainty is presented and explained, including sampling and value function approximation methods.

Chapter 7 presents results from the stochastic study of optimal investment strategy under R&D uncertainty. First, the optimal investment strategy under uncertainty is compared and contrasted with the optimal deterministic strategy. Using various probability distribution types for the outcomes to R&D, the effects of increasing skewness and overall level of risk (variance) on the optimal investment strategy is presented and discussed next. The impact of R&D effort risk profiles and technology characteristics is also discussed.

Finally, Chapter 8 summarizes the dissertation and its contributions, and recounts the key insights from both the deterministic and stochastic study of optimal R&D and capital investment planning (with and without uncertainty). The implications of this research to policy analysis and real-world planning within the electric power sector are explored and discussed. Major limitations of the new modeling framework are also presented, and important future research opportunities in this area are framed.

The dissertation now begins with an overview and history of the U.S. electricity generation and innovation system.

# Chapter 2 Overview and History of the System

The research questions under investigation in this dissertation take place at the intersection of the U.S. electric power system's generation sector and the U.S. energy innovation system's electricity technology-related activities. The engineering system studied can thus be described as the "U.S. electricity generation and innovation systems nexus". This chapter provides a background of the relevant structure and activities of each of these two sub-systems; each is a substantial system on its own. It also discusses some of the key uncertainties inherent in the system. It should be noted that while this dissertation does not resolve all of the structural details presented below (much is beyond the scope of the immediate research questions and the purpose of study), overviews are included here to provide the reader with a contextual background of the system and an appreciation of future research tasks and challenges.

## 2.1 The U.S. Electric Power Generation Sector

The U.S. electric generation sector is unique in many respects. The country's size, the specific evolution of physical infrastructures through time and space, and the nature of federal, state, and other regulatory authorities make the U.S. electricity landscape among the most diverse in the world. The generation sector fits within a larger physical electric power system, which is comprised of vast generation infrastructure resources (the power plants that produce the electricity supply), end-use infrastructure resources (the homes, commercial buildings, and industrial facilities that use the electricity supplied), and transmission infrastructure resources (the wires that move the electricity from the point of supply to the point of use). Likewise, it fits within a larger socio-technical system which is comprised of the physical components just listed, the numerous regulatory agencies that oversee its operations, markets (commodity and financial), and planning; businesses and public utilities that own and operate the physical infrastructure; customers that use the electricity for personal or other uses; and other stakeholders such as environmental non-governmental organizations that have vested interests in the activities of this highly influential (economically and environmentally) industry. Figure 2-1 provides a snapshot of the landscape of electricity generation facilities in the U.S., showing how generation density generally follows population density in the country. The size of the circles indicates the relative electricity output of the plants.

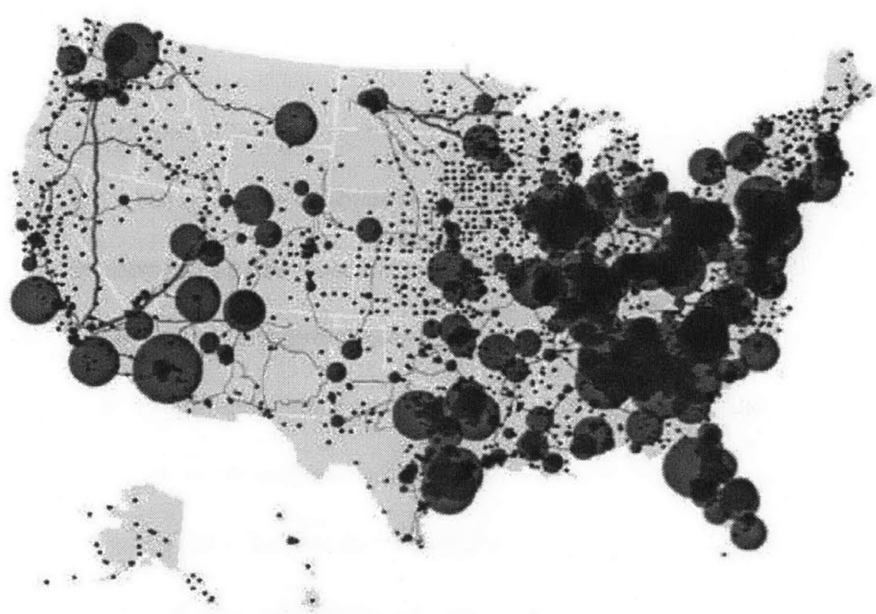

**Figure 2-1 Landscape of U.S. Electricity Generators**
(NPR.org, 2012, Original Source: EPA E-Grid Database)

The following subsections present an overview about the structure, functions, and general operation of the U.S. electric power generation sector. The types of resources used to generate electricity, facility ownership structures, unique characteristics of electricity as a commodity, generation planning functions, technology costs, legal and regulatory oversight structure, and the climate change policy landscape are reviewed and briefly discussed.

### *2.1.1 U.S. Generation Capacity Technology Portfolio*

As of 2010, there were 18,151 electric generating facilities in the U.S., which when combined, comprise the country's 1,128,638 megawatts (MW) of generating capacity (EIA, 2010a). Overall, the generating capacity portfolio in the U.S. is dominated by coal- and natural gas-fueled sources, with the majority of the difference supplied by nuclear power (Figure 2-2). This has been the general trend throughout U.S. electricity history (Figure 2-3). Hydroelectric power (conventional and pumped storage facilities) comprises nine percent of the resources, and other technology types (including all renewables resources such as wind and solar power) comprise the remaining five percent. Capacity additions to keep up with continually increasing demand and retirements of older plants (Figure 2-5) over the past fifty years have also focused on natural gas-fired, coal-fired, and nuclear-power generation, followed by a small surge in wind capacity during the past five years. In terms of actual generation (operation of the installed facilities), the balance shifts further towards fossil fuels. In particular, coal has provided a particularly inexpensive fuel source (Figure 2-4). Once a coal-fired power plant is installed, it tends to be utilized as a dominant resource, sometime referred to as "baseload", meaning it operates nearly year-round except for periodic maintenance. Nuclear plants similarly operate as baseload. As explained in more detail below, technologies such as coal or nuclear have relatively high capital costs, but relatively low operating costs, and these characteristics are the main drivers as to which units are baseload. In addition, technical constraints of the technologies that create challenges to rapidly shutting down or starting up or ramping power output up or down contribute to how these technologies are used. To date, renewable resource generation currently has had a minor role relative to the entire U.S. generation share.

There is great diversity of generation resources and associated fuel sources used to generate electricity across the country (Figure 2-6). Several factors influence this, including regional fuel availability, fuel price, environmental regulations, and political or public support for particular fuels. For example, the West Coast's abundant supply of "run-of-the-river" water results in its relatively higher share of hydropower compared to the West South Central region. The strict environmental regulations and lack of public support for coal-fired power generation in the West Coast region also creates a much smaller reliance on coal use than other parts of the country.

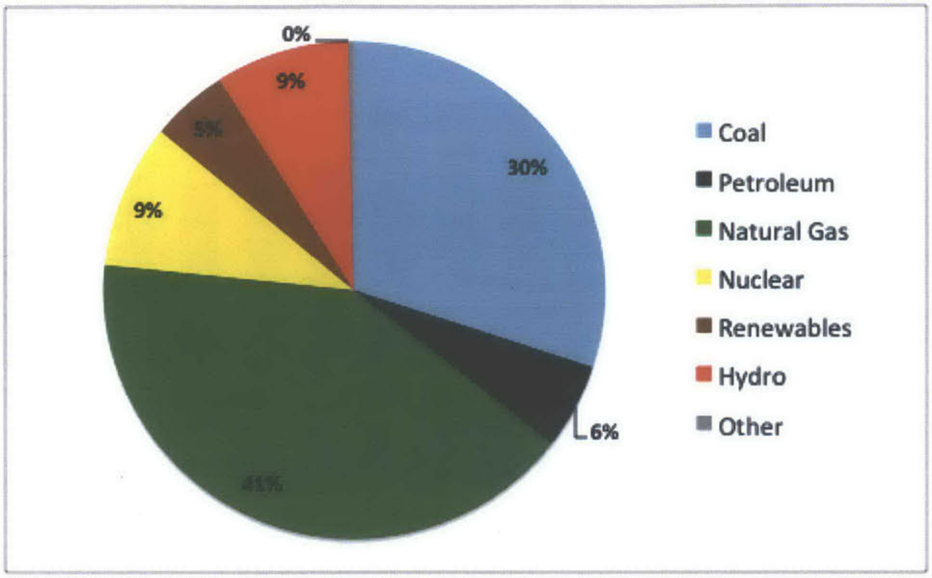


**Figure 2-2 2010 Electricity Generation Technology Portfolio (Installed Capacity)** (EIA, 2010a)

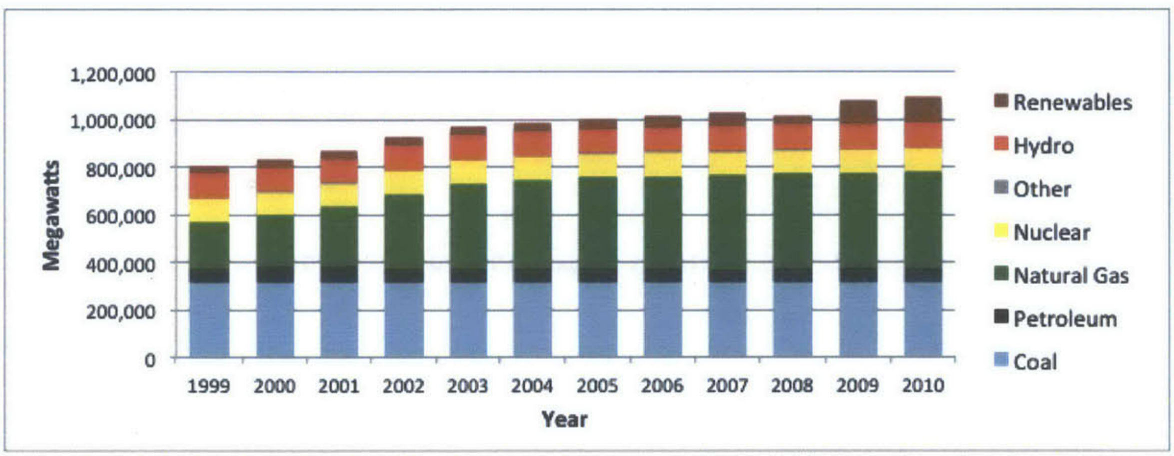


**Figure 2-3 U.S. Electricity Generation Technology Portfolio 1999-2010 (Installed Capacity)** (EIA, 2010a)

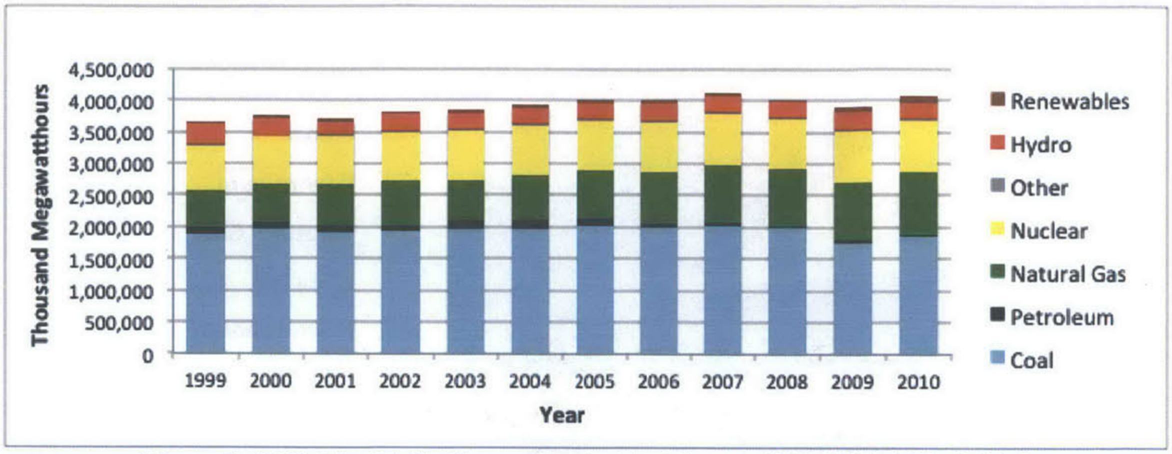

**Figure 2-4 U.S. Electricity Generation by Fuel Source 1999-2010** (EIA, 2010a)

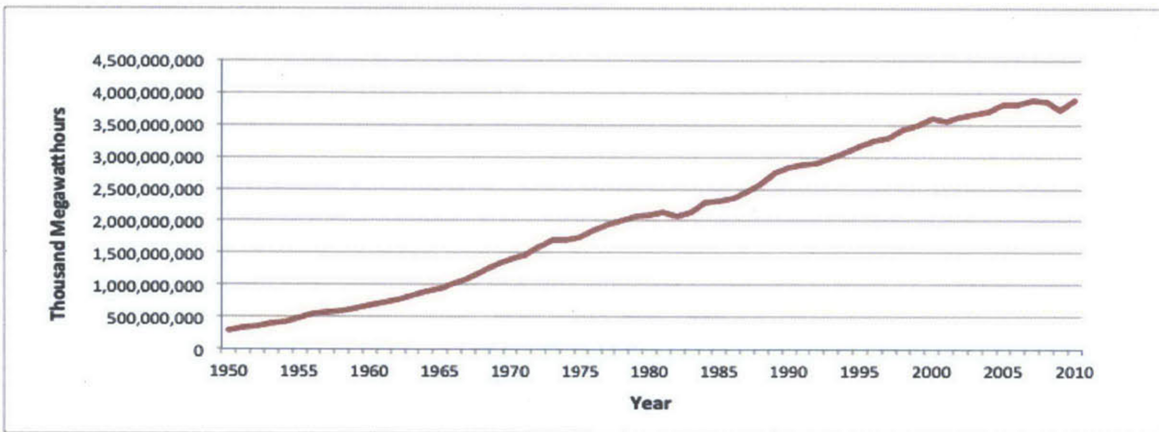

**Figure 2-5 U.S. Electricity Demand 1950-2010** (EIA, 2011a)

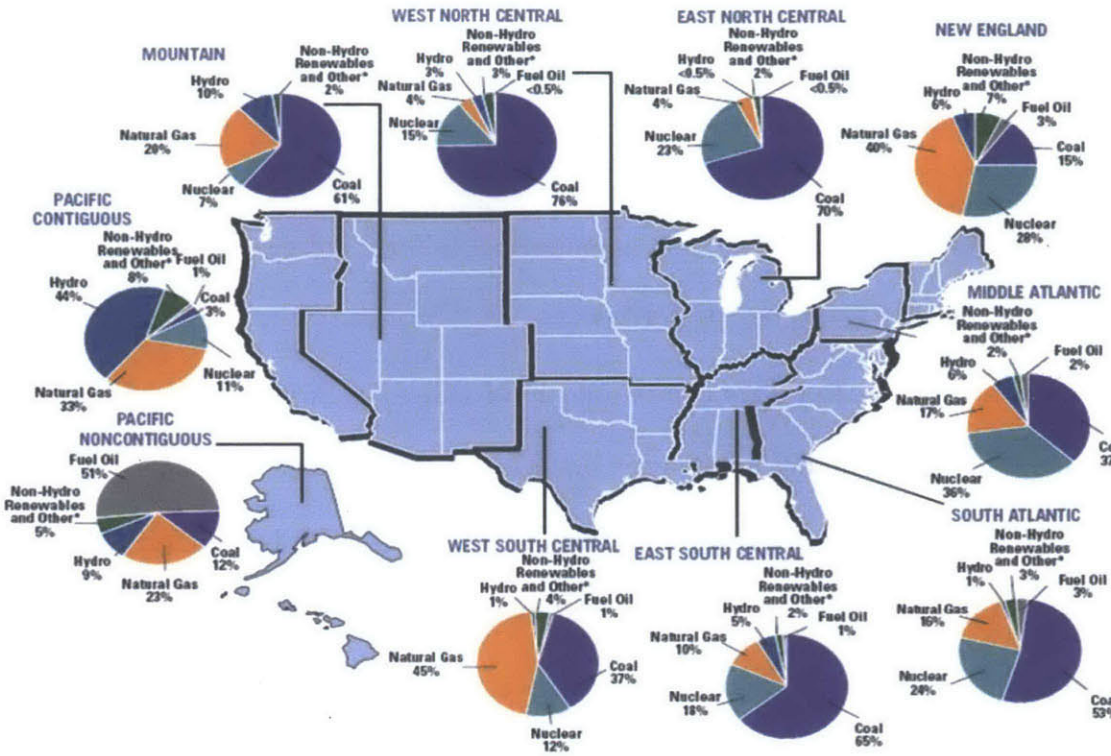


**Figure 2-6 U.S. Electric Power Generation Regional Fuel Diversity** (Edison Electric Institute, 2009)

### *2.1.2 Generation Ownership Structures*

Across the country, four main ownership structures exist, each with different levels of vertical integration (generation, transmission, and distribution facilities) within them: investor-owned utilities, publicly owned utilities (state and local government or public utility district owned), federally owned utilities, and rural electric cooperative utilities (Figure 2-7).

Although investor-owned private utilities comprise only about six percent of electricity entities, they produce over 65% of the electricity consumed in the U.S. on a total "sales-to-ultimate-consumer" (kilowatt hour) basis. Private power producers sell electricity at retail rates directly to end-use customer classes (industrial, commercial, and/or residential), and for resale at wholesale rates to other utilities. As shown in Figure 2-7, publicly owned utilities, on the other hand, comprise the vast majority of entities (approximately 60%), but they supply only about fifteen percent of the nation's power needs. Publicly owned utilities such as municipal utilities are generally self-regulated and financed through bonds. (EIA, 2007a)

Federally-owned utilities consist mostly of individual Army Corps of Engineers and Bureau of Reclamation hydropower projects scattered around the country, and the Tennessee Valley Authority, which operates generation and distribution facilities in the Tennessee Valley Region. Power generated at these federally owned facilities is sold mostly to publicly- owned and rural cooperative utilities at low (wholesale) rates, and surplus power is sold to the wholesale market. Rural electric cooperative utilities exist mostly as a result of the 1936 Rural Electrification Administration, created as part of New Deal legislation, which sought to expand electric power access to previously isolated rural areas. As of 2007, there were approximately 900 rural cooperatives in the U.S., most of which act as distribution utilities only, purchasing power for their customers from the wholesale market, and without their own generating facilities.

Additional (small) electric entities in the US consist mostly of individual cogeneration and other industrial "facilities" with generation sources that sell power directly to industrial or residential customers under regulated rates, and "other" power marketing entities or energy service providers who sell either energy or distribution services to end-use customers (EIA 2007a; Edison Electric Institute, 2009).

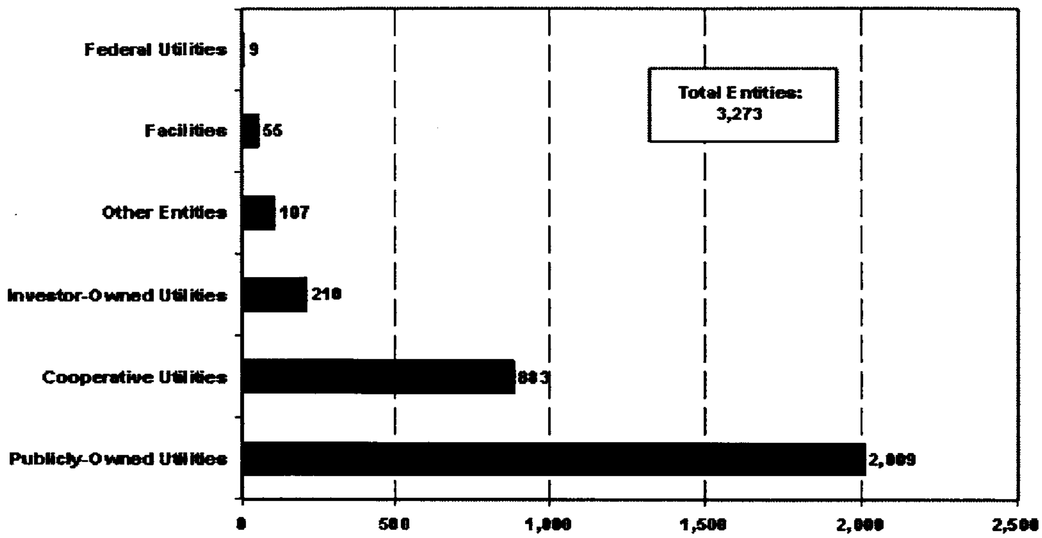


**Figure 2-7 Composition of U.S. Electric Utilities 2007** (EIA, 2007a)

### *2.1.3 Three Unique Characteristics of Electricity*

In the context of operating the electric power system and planning for the future of the generation sector, three unique and interrelated characteristics of electricity must be considered. First, unlike other commodities, at present, electricity cannot be effectively stored on a large scale, which creates severe inventory challenges. In practice, this requires that electricity be produced in "real time," as it is demanded; generators on the system respond to increased demand instantaneously by increasing their supply. From an operations standpoint, the lack of storage creates several challenges, including the need to maintain "spinning reserves" in order to maintain a margin above the current level of demand that can be met rapidly. From a generation capacity planning standpoint, this increases the importance of keeping a diverse portfolio of power plants—those which can provide power as baseload, as well as more flexible technologies that can be started and shut-down quickly.

Second, the power supplied must always equal the electricity demanded plus any transmission and distribution losses, in order to prevent power failures and system damage. From a capacity planning standpoint, this requires that power supply adequacy (size, number, availability, etc. of power plants) always remain ahead of demand.

Third, electricity system participants can only govern how much electricity is produced, how much is demanded, and the physical infrastructure (i.e., transmission grid and distribution wires) built to move the electricity around, but they cannot govern where the electricity flows once it is put on the grid (physical laws dictate this). From a capacity planning standpoint, this limitation increases the importance of generator locational siting with respect to transmission infrastructure and load centers, among other issues.

### *2.1.4 Electric Power Generation Planning*

The complex technical, economic, regulatory, and other institutional frameworks within which the electric power sector operates requires strong planning and modeling tools. A multitude of models and modeling methods exist; yet their relevance depends entirely upon the nature of the system being modeled and the nature of the inquiry. Power system expansion modeling is routinely performed by several entities, each seeking information that can inform very different types of questions. For example, the federal government may be interested in testing the implications of various policy proposals on the future U.S. generation portfolio mix (the interest of this dissertation) and least-cost pathways for reducing carbon emissions. Regional transmission organizations may be interested in forecasting capacity needs, given various demand projections. A transmission company may be interested in updating its long-range business plan and will need to estimate future production capacity on the system grid so that they can build new facilitating transmission lines. Finally, an individual generation company may want to plan its own firm-level long-range generation portfolio.

Power system operation and expansion planning modeling proceeds on many different levels and time horizons—from the very near term (in real-time, or on the order of seconds) to very long term (30-50 years into the future) (Figure 2-8). The economic dispatch function is on a shorter time scale (hourly) among the generation planning functions, but on a longer time step than near-real time generator control management (seconds to minutes) that keeps the system operating reliably. Economic dispatch describes how decisions are made to actually operate currently installed power plants to meet electricity demand. Above this function is unit commitment, which normally proceeds on the order of hours to a day in advance of actual generation, and consists of operators of the system and electric utilities confirming that specific generating facilities will be available (i.e., "on" or "off") to generate electricity during the next period in question. Electricity load forecasting is a necessary function within the generation planning hierarchy because, although inherently volatile, system operators need to be able to plan for how much generating capacity is needed to meet demand. At the longest time scale (years to decades) is the task of generation expansion planning, which is the function of making decisions about generating capacity to add to the system to meet future demand. This constitutes very long-term planning, and the electricity industry commonly employs cost-effectiveness analyses to do so, where the goal is to add new capacity at the lowest cost while still meeting overall system objectives such as reliability and/or sustainability.

Finally, there are interdependencies within this modeling hierarchy: each stage of planning directly depends upon the preceding step, increasing the importance of sound representations, estimations, and assumptions (Ramos et al., 2008; Ramos, Cerisola, & Latorre, n.d.). Modeling subsequent system functions requires that appropriate assumptions are made about all preceding functions. Because expansion planning—the focus of the larger research question in this work—is at the extreme end of the spectrum and requires assumptions about the processes at smaller time scales, special challenges exist for the long-range generation capacity expansion planner.

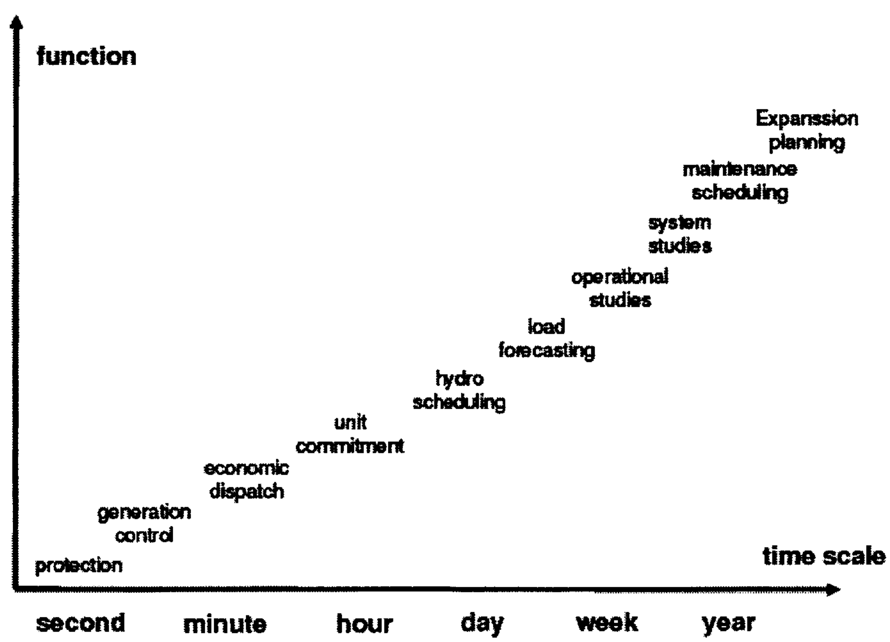


**Figure 2-8 Electric Power System Planning Functions** (Perez-Arriaga, Rudnick, & Rivier, 2009)

### 2.1.5 *Generating Technology Costs*

The generation capacity expansion problem is cost-driven. There are several additional objectives relevant to broader decision making about new capacity additions, but ultimately the decision comes down to a question of costs. Currently, the range of costs associated with technologies capable of generating electricity is very wide. Moreover, there is a high degree of variability between the different types of costs that comprise the total cost structure for a given technology, and it is the combination of these different costs that allows the expansion planner to choose between different installation plans. Several estimates exist for the costs of different technology types (a result of companies' reluctance to publicly reveal the final values they end up paying to install and operate different technologies, and of the different methods and sources for data collection). Figure 2-9 shows examples of capital, fixed operation and maintenance, and other variable costs across different technologies as used by the National Renewable Energy Laboratory (NREL) (Short et al., 2009) and the U.S. Energy Information Administration (EIA) (EIA, 2010b).

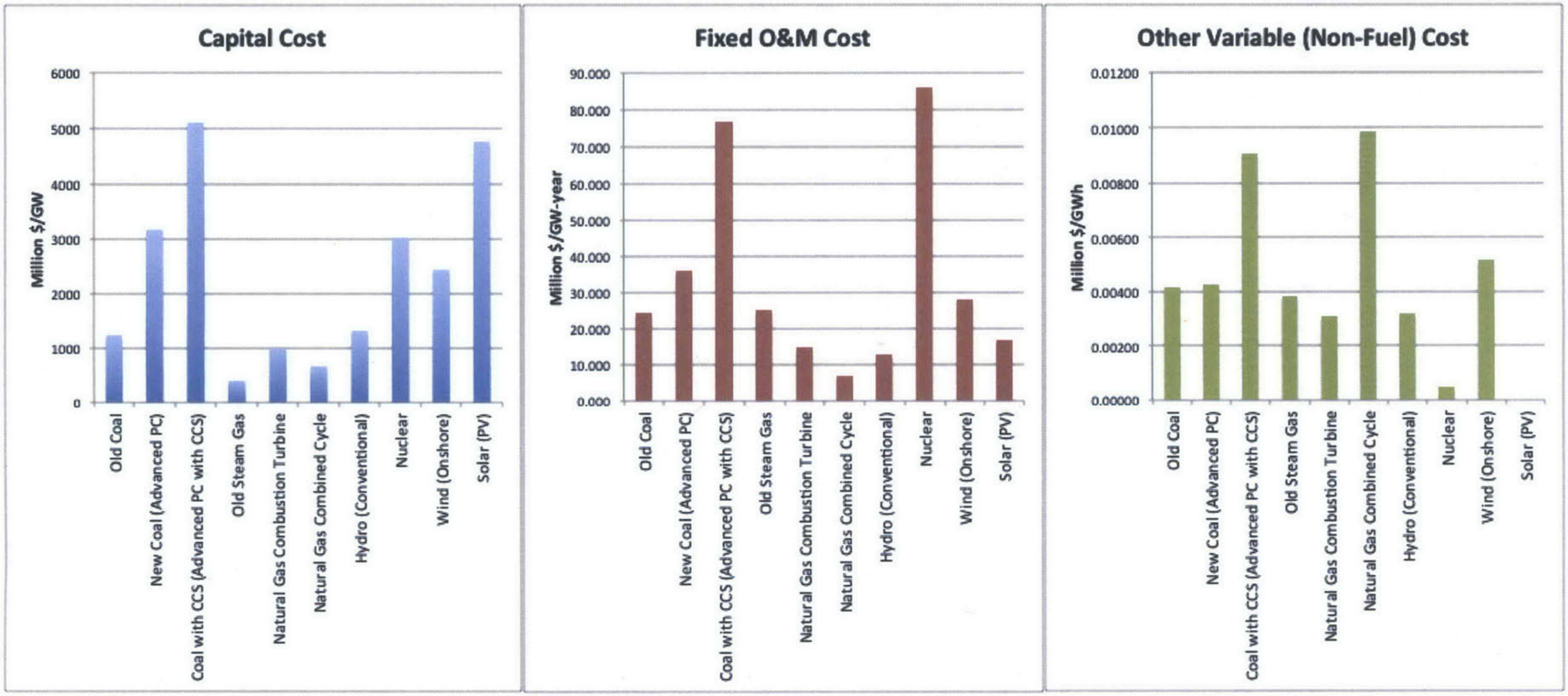


**Figure 2-9 Capital costs (a), fixed operation and maintenance costs (b), and variable costs (c) for various electricity generation technologies** (Data Sources: Short et al., 2009; EIA, 2010b).

At present, new advanced coal plants, coal plants with carbon capture and sequestration technology, nuclear power plants, and large solar photovoltaic plants remain the most capital intensive and costly plants, while also being the least expensive options regarding fuel-based variable operating costs. Natural gas plants follow an opposite pattern, with relatively low capital costs, but historically high natural gas prices (and relatively volatile gas prices, making planning for their expansion and operation challenging). As of the last decade however, new drilling techniques *have* allowed for enormous increases in production of natural gas from shale formations in the U.S., which have helped keep natural gas prices quite low and less volatile (Figure 2-10). Wind power remains relatively moderate with respect to capital costs and free with respect to fuel costs (renewable wind).

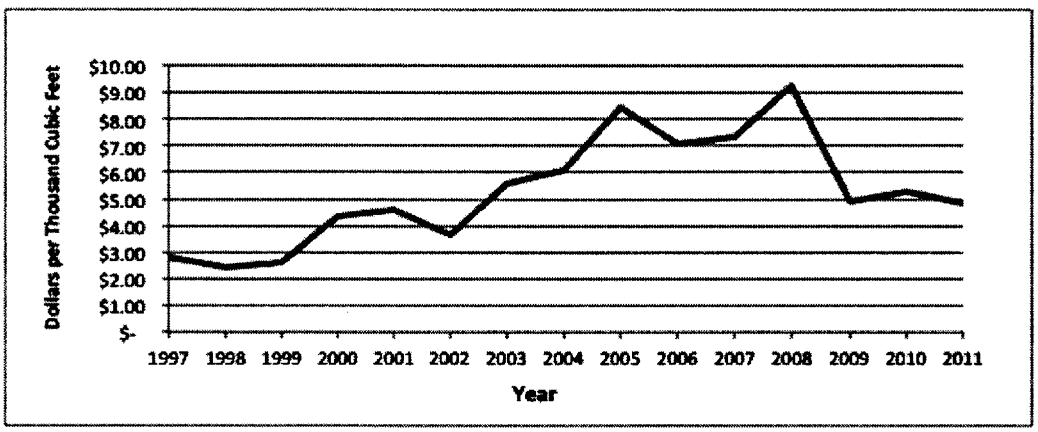


**Figure 2-10 Natural Gas Prices Paid by Electric Power Sector 1997-2011** (EIA, 2012a)

When combined, these fixed capital and variable fuel costs (and other costs) are used to determine the least-expensive manner in which to meet electricity demand. For example, the relatively high capital cost of a coal plant but low fuel cost makes it an ideal choice for meeting the baseload of electricity demand—once a coal plant is installed, it is very economical to run, so it should run most of the time. An additional relevant technology-related feature for the generation expansion planning problem is the availability of the fuel resource, particularly in the case of wind power or solar power. In the case of wind power, for example, the capital cost is modest, and the fuel price is zero, but the wind resource remains an intermittent and less reliable source of energy than other energies, which limits its ability to be widely adopted at large scale.

These different technology characteristics lay the foundation for how different generation technologies within the power system balance each other, and why a diverse portfolio of technologies is often the most economical: build as much of the capital intensive, low fuel cost technologies as can meet the base-level of electricity demanded during a day, or a year, etc., and then begin matching subsequent quantities of electricity demanded and the amount of time it is needed with the technology that is most economical to build and operate for that amount of time. Using such a "screening curve" approach usually results in technologies such as nuclear, coal, and hydropower plants being built and operated to meet baseload electricity demand, natural gas combined cycle plants being built to meet "shoulder" electricity demands, and natural gas open-cycle plants being built to meet the highest, peak levels of electricity demand. Renewable resources such as solar power and wind power remain relatively isolated from traditional screening curve analyses, as their primary energy resources are intermittent and they are usually utilized whenever available. The rest of the system then adjusts.

### 2.1.6 *Electricity Industry Regulation and Oversight*

Several government and quasi-governmental agencies at the federal, regional, and state level oversee the generation sector of the U.S. electric power industry. At the federal level, the main bodies of oversight and support include the Federal Energy Regulatory Commission (FERC), the Environmental Protection Agency (EPA), and the Nuclear Regulatory Commission (NRC). FERC is mainly responsible for the oversight and approval of wholesale electricity and transmission rates in interstate commerce. EPA oversees and administers most environmental regulations affecting generation facilities, including technology standard setting for new generating facilities (e.g., minimum air and water emission limits) and pollution compliance programs. NRC oversees virtually all aspects of the civilian nuclear power program in the U.S., including reviewing and approving proposals for new plants, re-certification of plants, and decommissioning of old plants. To a lesser extent, but still overseeing specific industry and market practices, are the Federal Trade Commission (FTC), the Department of Justice (DOJ), and the Commodity Futures Trading Commission (CFTC).

At the state-level, the main authorities include Public Utility Commissions (PUCs) and other state commissions, and the appropriate state-level environmental agency or agencies. PUCs in each state are responsible for regulating rates and services of public electric utilities. Often, they are multipurpose commissions and oversee a wide range of public utilities such as natural gas, water and wastewater, telecommunications, and transportation and safety, in addition to electricity. State environmental agencies, such as the Texas Commission on Environmental Quality (TCEQ), California Air Resources Board (CARB), and Massachusetts Department of Environmental Protection

(MassDEP), typically administer federal regulations governing generation facilities (e.g., federal pollution permit programs), and also retain authority to enact more stringent state-level environmental regulations if desired.

In addition to federal, state, and sometimes even local regulatory authorities, the U.S. electric power industry is divided into three levels of regional regulatory oversight. The first level consists of the physical power grids, and does not directly involve the actual generation resources. The continental U.S. consists of three separate power grids, which operate simultaneously and at the same frequency, but not synchronously, and therefore they require special interchanges to connect them (Figure 2-11). Alaska and Hawaii operate on separate systems: Alaska operates a traditional grid that connects its major urban areas, various mini-grids, and smaller isolated diesel generators. Hawaii consists mainly of non-interconnected mini-grids and isolated generators for powering individual islands. The lack of synchronous operation between the three main power grids in the continental U.S. makes coordination and planning between them an often challenging task (U.S. Department of Energy, 2009).

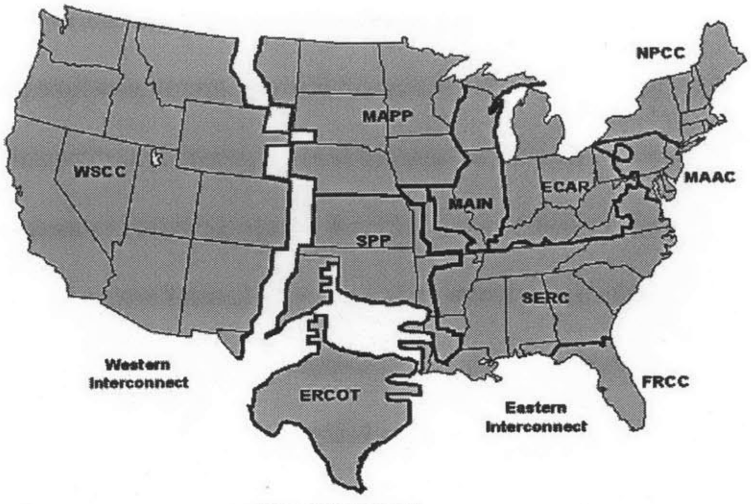


**Figure 2-11 U.S. Power Grids and NERC Reliability Regions** (U.S. Department of Energy, 2009)

The next level of oversight is also shown in Figure 2-13, and consists of the North American Electric Reliability Councils (NERC regions). There are ten in the US plus Canada, which are structured to oversee reliability, and security of generation resources and electricity supply. Utilities within each NERC region coordinate planning and operations in order to maintain a suitable level of electricity supply security and reliability. Finally, the industry consists of several Regional Transmission Organizations (RTOs) (also known as Independent System Operators (ISOs)) that operate throughout North America. The Federal Energy Regulatory Commission organized and developed RTOs to formally replace former informal power pools, which used to exist to exchange power and coordinate planning and operation between regional grid areas (Figure 2-12).

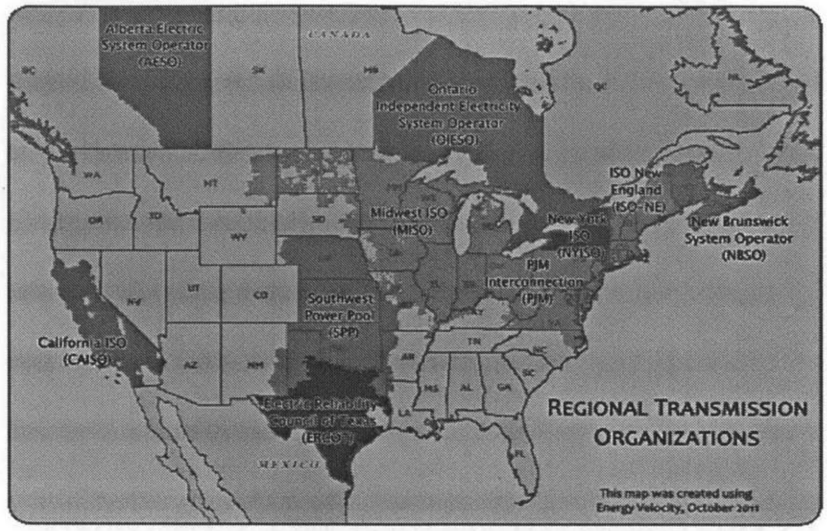


**Figure 2-12 Regional Transmission Organizations in North America**
(Federal Energy Regulatory Commission, 2012)

Given the comprehensive coverage of regulations and legal oversight of the electric power industry, it is perhaps surprising that there is any discussion about deregulation in the U.S. First, it must be noted that the term "deregulation" is an often misapplied word in this context; in the electricity sector deregulation applies only to the generation sector (and even then only to a portion of the generation sector). U.S. interest in deregulation was spawned in the early 1990s for a variety of reasons that are beyond the scope of this system overview, but its basic tenet was the substitution of market prices for previously government-set consumer retail rates for electricity. In deregulated markets across the U.S., generation sectors have been restructured and customers can make the choice about their electricity supplier. Currently however, the U.S. struggles in a state of disequilibrium, about half-way between a highly regulated system dominated by local monopolies and a deregulated system where electricity prices and generation capacity investment decisions are set primarily by competitive markets (Figure 2-13). At the state level, several states have active, restructured industries; yet others that had originally started down the deregulation path have suspended their restructuring efforts for a variety of reasons. In the near term, and what is relevant for generation expansion planning, the U.S. will continue to see a hybrid system of regulation and competition, making the planning job even more challenging.

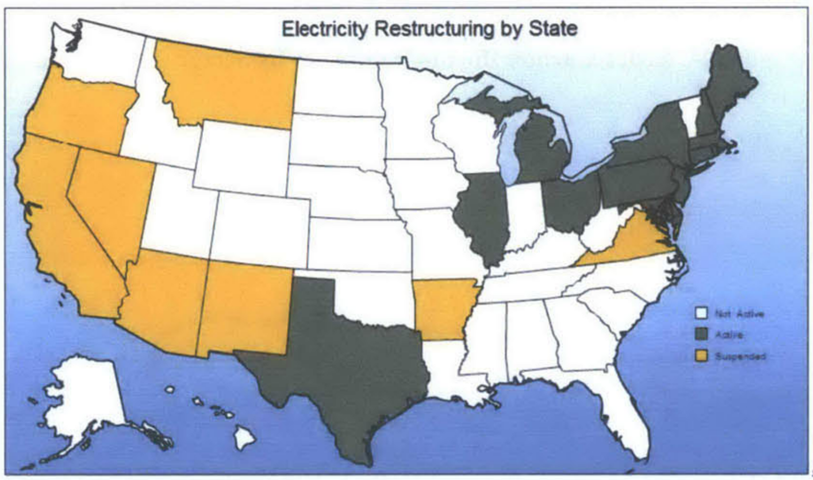


**Figure 2-13 Status of U.S. Restructuring by State** (EIA, 2010c)

### *2.1.7 Climate Change and the Policy Landscape*

In 2011, the U.S. electric power generation sector emitted approximately 2000 million metric tons of carbon dioxide into the atmosphere, representing about 40% of the country's $CO_2$ emissions—the most abundant anthropogenic greenhouse gas. Emissions from the transportation sector follow closely behind, with all other sectors representing a smaller fraction (Figure 2-14). This trend has been consistent throughout recent history (Figure 2-15).

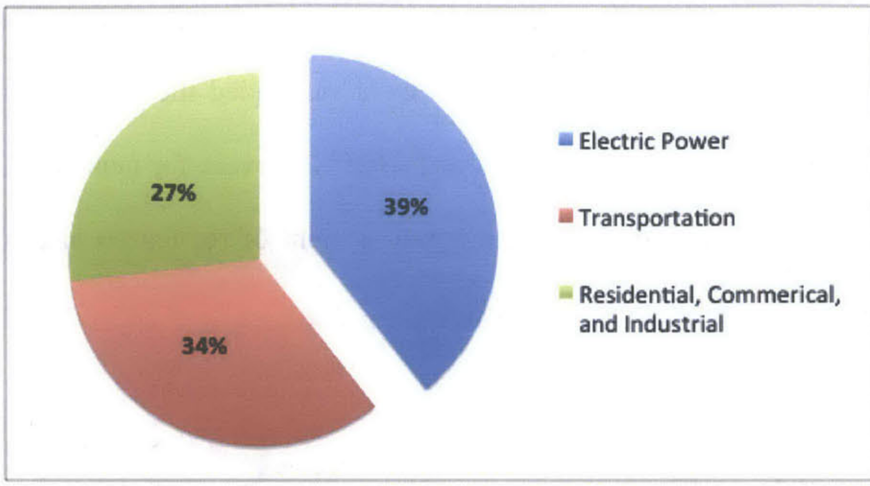


**Figure 2-14 2011 Carbon Dioxide Emissions by Sector** (EIA, 2012b)

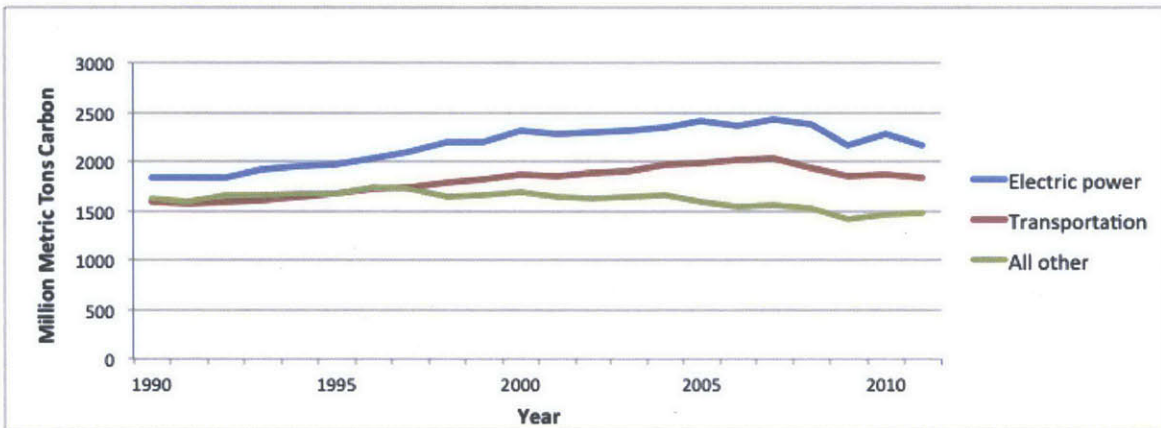


**Figure 2-15 Carbon Dioxide Emissions by Sector 1990-2011** (EIA, 2012b)

Until 2006, the U.S. was the largest emitter of the $CO_2$ in the world (only recently superseded by China as the world's largest emitter during the past five years), and remains the largest cumulative contributor of $CO_2$ in the atmosphere. Figure 2-16 illustrates the relative proportion of U.S. $CO_2$ emissions compared with other major emitting countries and with the rest of the world. When the data in this figure is combined with the share of electric power emissions from Figure 2-14 above, it can be shown that the U.S. electric power industry accounts for roughly 10% of $CO_2$ emissions from the world's top emitters. Thus, planning for a sustainable and low carbon U.S. electricity generation sector constitutes a non-negligible size of the entire world's $CO_2$ mitigation effort.

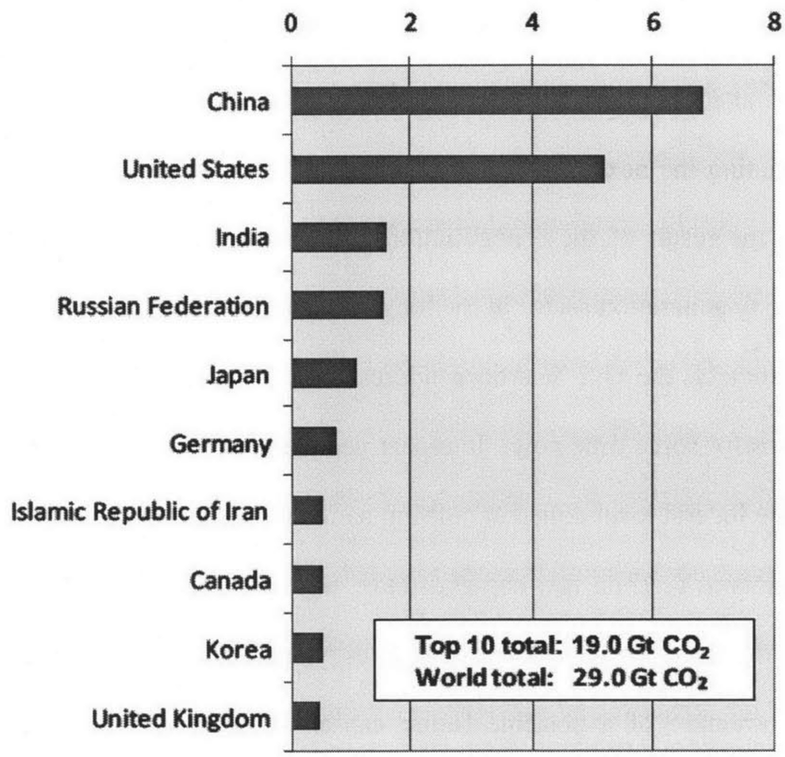


**Figure 2-16 World's 10 Largest $CO_2$ Emitters (in Gigatons) 2009 © OECD/IEA (IEA, 2011)**

Cognizant of this need, the world and the U.S. have produced a flurry of political and technical proposals about how a transformation to a low-carbon world electricity sector might proceed. On the policy front, in 1992 the United Nations Framework Convention for Climate Change (UNFCCC) outlined a process for global coordination towards stabilizing greenhouse gas concentrations in the atmosphere at a level that would prevent dangerous anthropogenic influence with the Earth's climate system. As one step in this process, the Kyoto Protocol was agreed to in 1997 and ratified by 160 countries (the United States not included). The Protocol went into force in 2005 and as of January 2009, 183 parties had signed on to it. It called for a roughly 5% reduction in collective greenhouse gases from industrialized countries relative to their 1990 emissions. The Kyoto protocol expires at the end of 2012, and discussions about its extension or re-ratification are at present moving forward slowly. The world's climate change leaders are still negotiating the next installment of a global treaty on greenhouse gas reduction. But whatever the result of these negotiations, the importance of a transition to a low carbon electricity generation sector in the long-run is well-known.

Domestically, the U.S. has been addressing climate change and greenhouse gas reduction issues for some time now. In recent years, there has been a surge of legislative proposals at the federal level aimed at curbing national greenhouse gas emissions through various mechanisms (carbon tax, cap-and-trade, etc.). In June 2009, the U.S. House of Representatives passed the American Clean Energy and Security Act (ACES Act), which set forth the structure of a possible future cap-and-trade program for $CO_2$ and other greenhouse gas emissions, including those from the electric power sector. Targets for emission reductions were stringent, and the distribution of allowances for the electricity sector decreased over time until reaching zero by about 2030, pointing once again to the imperative nature of electric power generation technology reform. To date, neither ACES nor any other climate policy legislation has been enacted.

While the country waits for future national climate policies to be decided, regional, state, and local governments have proceeded to address climate mitigation through their own initiatives. Twenty-nine states and the District of Columbia have renewable electricity generation portfolio standard mandates (RPS) and five more states have voluntary renewable goals (**Figure 2-17**). Additionally, regional greenhouse gas cap-and-trade programs such as the Western Climate Initiative and the Regional Greenhouse Gas Initiative (RGGI, in the Northeast) were developed and some are already operating. Other non-federal partnerships, such as the U.S. Mayors Climate Protection Agreement, where cities pledged to meet Kyoto-like greenhouse gas reduction targets (seven percent below of 1990 levels by 2012), have been created.

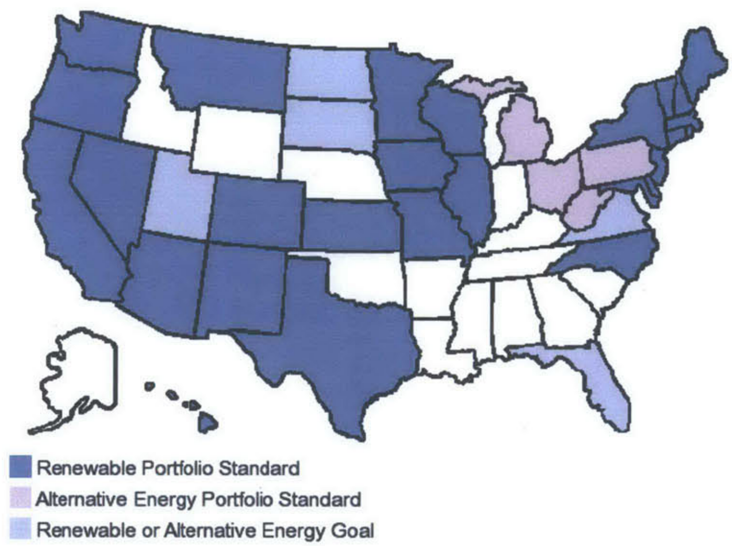


**Figure 2-17 U.S. State Renewable and Alternative Energy Standard Program Status**
(Pew Center on Global Climate Change, 2009)

Meeting even modest climate targets will require major changes in the electric power system; some of these have already begun taking place. The first, most striking, and highly influential change is the exponential growth in generating capacity using low-and zero-carbon emitting renewable resources (Figure 2-18), most of which is due to rapid increases in new wind power facilities. Although this increase still only results in a total renewable capacity of 5% of total generating capacity in the U.S., this relative capacity growth (and associated operation) still affects the overall system in meaningful ways. One important effect is the need for system operators to manage an increased level of intermittent electricity generation with zero-emissions with a lower resource availability rate compared to conventional fossil and nuclear plants. This complicates capacity planning by increasing the need to create balanced portfolios of technologies for reliably meeting demand.

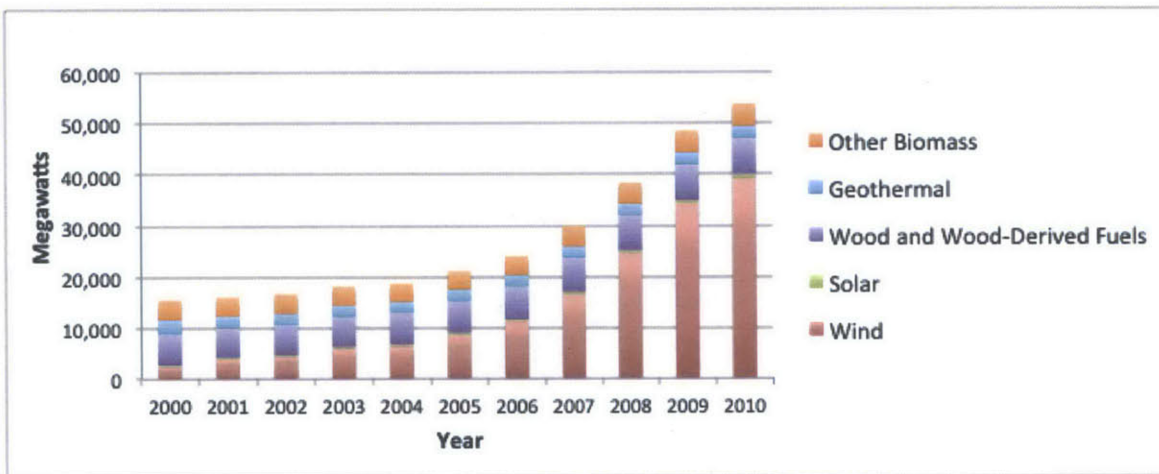


**Figure 2-18 U.S. Renewable Electricity Technology Capacity Trends 2000-2010** (EIA, 2010a)

Other key technological prescriptions for the system to help transition the generation sector to a low-carbon state—some of which have already begun moving forward—include an increase in distributed generation resources such as small facility wind-turbines and residential and commercial-top roof solar photovoltaic panels, the growth of battery-electric vehicles in the transportation fleet, and serious consideration of integration of carbon capture and sequestration technology into fossil fuel-fired power plants on a large scale. Each of these prescriptions, however, including the continued addition of more renewable resource capacity, will require continued technological advances, and in some cases technological breakthroughs. Large-scale carbon capture and sequestration at coal and natural gas plants needs additional research due to its high capital cost relative to other conventional technologies. Adding more and more wind power to the system will require the use and integration of other technologies to help balance its intermittency. Integrating new technologies such as battery-electric vehicles and large amounts of distributed generation would enable efficient large-scale electricity storage on the system, but would require a radical technology shift in the transmission and distribution sub-systems as well.

## 2.2 U.S. Electricity Innovation Activity

Technological change that would enable generating electricity more efficiently, at lower cost, or using radical new processes or scale-up of technologies, will require research and experience at several different stages. Broadly, technological change encompasses the invention, innovation, adoption, and diffusion of a technology from the laboratory to the point of commercialization and deployment. These phases loosely correspond to a learning-by-searching process followed by a learning-by-doing process, although there is considerable overlap and feedback between the two. In general, learning-by-searching can be considered the early innovative phases of a new technology or process, through invention and innovation. Learning-by-doing technological change generally occurs through demonstration and use of the technology once it is ready or almost ready for deployment. Formal efforts to increase efficiencies, reduce costs, or develop new processes or technologies through R&D programs usually occur in the learning-by-searching process.

Regardless of the pathway for technological change, several studies have called for the need to significantly increase the pace of energy technology change if a serious effort to manage climate change is to be made (Henderson & Newell, 2010). In fact, this need is very clearly seen in some of the most widely used energy systems and emissions forecasts used to inform policy making today. In the 2010 U.S. Energy Administration's reference case forecast, U.S. energy consumption increases 13 percent and carbon dioxide emissions increase 9 by 2030, which would exceed the range of carbon emissions targets proposed at the national level (Henderson & Newell, 2010). As another example, the reference scenarios of the International Panel on Climate Change (IPCC) reports assumed that two-thirds of all the energy efficiency improvements and de-carbonization technologies needed to reach climate stabilization targets would occur in the absence of additional climate policy beyond the status quo (Pielke et al., 2008). Pielke et al. (2008) argue that this assumption implies that the amount of technological change actually needed is even more than is often assumed.

The following subsections provide a general background of U.S. energy innovation activity, with a focus on electricity-related technologies. Brief accounts and overviews of the U.S. record of electricity innovation; current technology hurdles; key players in the innovation system; past and present R&D funding levels and trends; and key technology policy tools are presented.

### *2.2.1 U.S. Record of Energy Innovation*

The U.S. has a good record of innovation in energy technologies that it can build upon, particularly with electricity generation innovation. Consider the case of the advanced, combined-cycle natural gas-fired turbine, a technology that has provided the greatest efficiency gains in the electricity generation sector of any single technology type. The civilian nuclear power program provides another example. Building upon earlier, mostly military R&D investments, capacity additions of nuclear power experienced a dramatic increase in the 1960s and 1970s in the hopes of being a reliable, low-cost source of domestic energy (Newell, 2011). Although nuclear capacity has slowed tremendously since the 1980s for a variety of reasons, there has been a resurgence in interest in developing the next generation of nuclear plants with higher temperatures, higher efficiencies, and lower fuel-use (and lower overall costs). Finally, the case of wind power in the U.S. shows an example of successful R&D efforts. Since the early 1970s, when a major effort at wind power innovation and deployment was made by the U.S. federal government and some non-governmental partners, dramatic shifts in the technology have taken place and wind turbine deployment has accelerated, due to decreasing costs, government subsidies, and tax credit programs. Whereas early wind turbines were small—generating about tens of kilowatts with 15 meter diameter rotors—the use of lighter-weight materials and capability to operate at variable speeds has allowed recent wind turbines to generate up to 2.5 megawatts using rotors closer to 100 meters in diameter. These increases in scale have also lowered the cost of generating electricity from a wind turbine from almost 30 cents per kilowatt hour in the 1980s to 10 cents per kilowatt hour in 2007 (Newell, 2011).

### 2.2.2 *Technology Hurdles*

Similar types of transformations need to occur—some on a much larger scale and faster timeline—if significant carbon reductions are to be achieved. Technologies requiring further improvements include carbon capture and sequestration, advanced nuclear, solar, and wind. For coal- and natural gas-fired power plants with carbon capture and sequestration (CCS), the major hurdles require addressing efficiency losses that occur in the capture process, and reducing the associated high investment costs. Currently, fewer than ten large-scale demonstration projects exist, but almost ten times more are needed to rigorously prove the technology is viable at the scale needed. (Several non-technical hurdles for CCS also exist, including the need to establish legal and regulatory frameworks for stored carbon dioxide, international collaboration to learn about the technology faster, and integration of CCS technologies into future climate policies.)

Nuclear (fission) technology is already proven at scale, but there is a current push to build new plant designs that can operate at higher temperatures (and achieve greater efficiencies and reduce fuel use and waste output), thereby lowering costs. Non-technical hurdles also exist for nuclear power technology, including a need to establish permanent long-term storage of spent fuel, and overcome various political constraints associated with nuclear power safety concerns and fuel storage.

In terms of solar power, innovation goals for concentrating solar power technology include cost reduction by increasing scale (e.g., plants with 100+ concentrating dishes), higher electricity storage capacities, and higher operating temperatures. For solar photovoltaic (PV) technology, needs include basic materials and chemical engineering innovation to increase performance, as well as designs for increasing scale. For wind technology, the technology change focus continues to be on lighter and stronger materials for all wind power subgroups. New innovations are also needed in basic materials to achieve large scale deep-water off-shore wind installations (e.g., adequate corrosion-resistant materials for ocean applications). (IEA, 2010; Herzog, 2011)

### *2.2.3 Key Players in R&D*

Electricity-related R&D funding comes from several different sources. At present, R&D activities are pursued in a variety of modalities. The U.S. Department of Energy (DOE) provides almost 90% of the federal government's energy funding to national laboratories, universities (usually through grants), and co-funded collaborative research projects with utilities and equipment manufacturers. The balance is made up of funding from the National Science Foundation (NSF), National Aeronautics and Space Administration (NASA), and a range of Executive Agency Departments (ITIF, 2010). National lab research is usually targeted at basic energy science, although funding for applied science has also been granted (albeit in a less committed and more volatile manner) (Anadon et al., 2010). Two new federal energy R&D institutions include the DOE Energy Innovation Hubs (DOE EIH) and the Advanced Research Projects Agency – Energy (ARPA-E). The DOE EIH program mission is to integrate basic and applied R&D efforts to reach commercialization of important energy technologies. ARPA-E is focused on high-risk, high-reward innovation, acting as a funding mechanism for projects that seek to develop the next generation of energy breakthrough technologies. Both institutions provide multi-year (3+) funding commitments for projects (Anadon et al., 2010).

Historically, electric utilities themselves played a significant role in funding R&D activities (mostly applied research), but this has waned in recent years. This shift occurred for a variety of reasons, but one important driver has been deregulation and increased competition. In the past, public utilities, which were mainly regulated monopolies, could receive approval for including R&D expenditures in their rate base, which allowed them a fixed rate of return on those expenditures. However, this is no longer the norm (GAO, 1996). Private and investor-owned utilities continue to partake in R&D activities, as do state programs (although both to a lesser extent than the federal government). Private equipment manufacturers constitute the other major source of R&D funds, although estimates of their spending are proprietary and thus usually unavailable in a form sufficiently disaggregated to be useful. A 1988 study by the Electric Power Research Institute estimated that private equipment manufacturers spent a total of $200 million on electricity-related R&D (GAO, 1996).

The story of the innovation behind the advanced combined cycle gas turbine provides a useful example of the heterogeneous efforts that mark the present innovation landscape in the power sector. When the Advanced Turbine System (ATS) program was launched in 1992, a long-term (8-year) R&D program was outlined and agreed to by all participating parties, totaling approximately $750 million. Two simultaneous programs were launched, one by General Electric Power Systems and the other by Siemens Westinghouse Power Corporation. In both cases, nine different groups participated in the R&D effort. In the case of the GE turbine design program, GE partnered with DOE national laboratories and the DOE program management, utility companies and power producers, university research programs (through research grants), vendors, casting companies, and other GE business groups including GE Aircraft Engines and GE Corporate Research Division (Curtis, 2003). A similar set of groups participated in the Siemens Westinghouse effort.

### *2.2.4 R&D Funding Levels and Trends*

Although institutions across the country exist to perform energy R&D activities, adequate funding to do so has been a different story. As of 2007, the U.S. invested $1 billion less annually than it did a decade earlier in electricity sector technologies, as well as across the energy industry (Nemet & Kammen, 2007). In fact, both public and private R&D investments declined dramatically between the early to late 1980s and mid-2000s, with public R&D funding declining more rapidly (Figure 2-19).

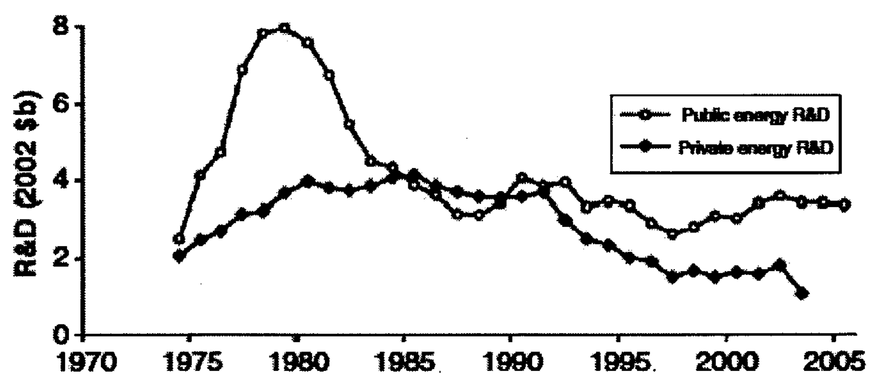


**Figure 2-19 U.S. Public and Private Energy R&D Trends 1975-2005** (Nemet & Kammen, 2007)

Two troubling features of this declining investment in energy innovation is that 1) it was counter to the country's overall R&D spending, which grew by over 5% per year, and 2) the amount of energy R&D spending compared to R&D spending across other sectors of the economy has always been low (less than 10% of total spending) (Nemet & Kammen, 2007; Margolis et al., 1999; Henderson and Newell, 2010). The decline in private R&D investments is especially challenging because in the past private companies and manufacturers were a reliable source of funding. The three main drivers behind this decline included the slow but continuing shift from regulated monopolies to competition, the decline of interest in nuclear power as a "savior" zero-carbon energy source due to concerns about waste, safety, and project cost overruns, and policy uncertainty (Nemet & Kammen, 2007).

More recently, this trend appears to be reversing and in 2010 overall energy innovation spending grew, from $3.2 billion in 2009 to $3.4 billion. During these years, an additional $4 billion was allocated to energy innovation projects through the American Recovery and Reinvestment Act (ARRA). The percentage of these funds devoted to electricity generating technologies is also considerable—approximately 50%--and were spread across a diverse set of technology categories (Figure 2-20) (ITIF, 2010).

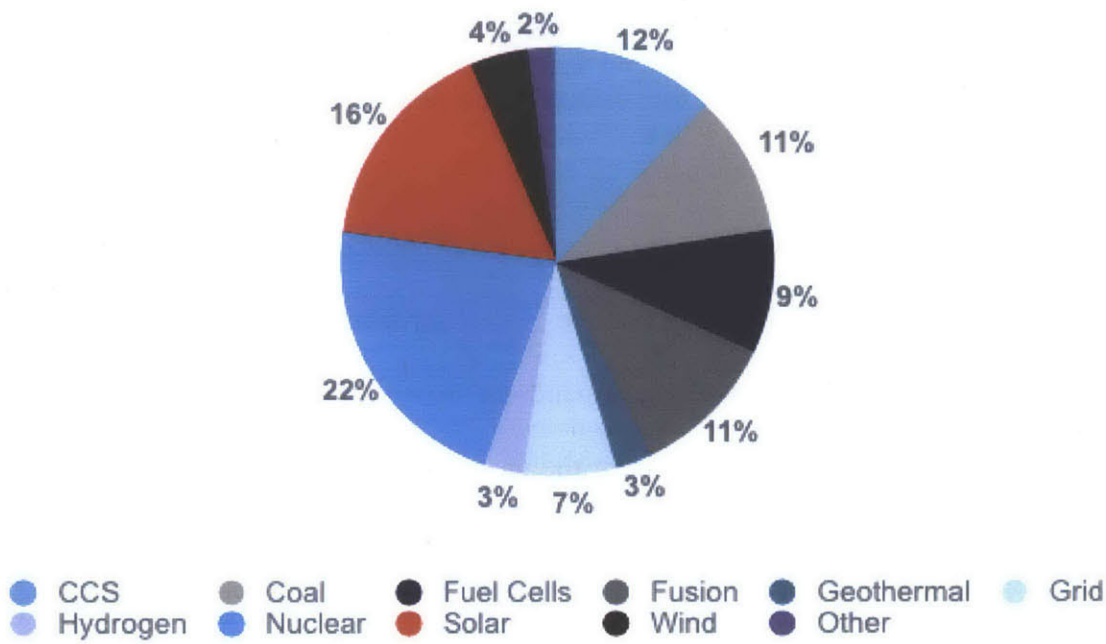


**Figure 2-20 2010 Electricity Technology Spending by Technology Category**
(ITIF Energy Innovation Tracker, 2010)

When considering total electricity-related support (including direct expenditures, subsidies, and tax expenditures), the 2010 estimate grows to $11.9 billion, an increase from $7.7 billion in 2007 (EIA, 2011c).

### *2.2.5 Technology Policy Prescriptions*

Technology policy as a means to stimulate a transformation to a low-carbon electricity sector is a much-discussed topic with respect to climate change mitigation and overall climate policy. Throughout the economic literature on technological change about the public role in energy innovation, two dominant roles exist: 1) to stimulate a market for technological improvements through policy interventions such as environmental regulation or a carbon cap and trade program, and 2) to directly support R&D activities to bring new technologies to the market (e.g., Newell, 2011; Henderson &

Newell, 2010; Fischer, 2009; Pew Center of Global Climate Change, 2008; Anadon et al., 2010). These two roles reflect the frequent "demand-pull" and "technology-push" prescriptions for technological change.

Demand-pull incentives refer to changes in the market, which lead to more of a certain type of technology being demanded. New environmental regulations, among many other things, can influence the demand for new technologies. For example, a pricing scheme for carbon emissions from the energy industry will increase the demand for many low-carbon electricity technologies, as firms directly affected by the new regulations look for ways to decrease costs of compliance. This increase in demand will signal the potential for increased profits to private inventors upstream, thus incentivizing them to innovate (Fischer, 2009).

The Federal Interconnection Standard implemented in 2003 and adapted in 2005 is one current example of a regulation that promotes the use of renewable electricity generation. Other common demand pull incentives for electricity generation technology deployment include state-level renewable portfolio standards that mandate a minimum level of renewable resource generating capacity to be online by specific dates, capacity payments for generators that participate in special "capacity markets", tax credits or production subsidies paid directly to utilities for installing certain qualified new technologies, low-interest loan programs, and demonstration projects (Pew Center for Global Climate Change, 2008). An example of a subsidy program is the US Department of Treasury Renewable Energy/ARRA Grant Program implemented in 2009, which awarded up to 30% of the property (i.e., equipment and property costs) for qualified fuel cell, solar, or small wind turbine facilities. Specific examples of current tax incentives programs are the federal Modified Accelerated Cost-Recovery System (MARCS) corporate depreciation program, which allows businesses to recover investments in certain renewable energy properties through depreciation deductions. Another is the Business Energy Investment Tax Credit (ITC), which provides a 30% tax credit for qualified solar, fuel cell, and small wind facilities, and 10% for qualified geothermal, micro-turbines, and combined heat and power applications. (DOE, 2012)

Perhaps the most well-known renewable energy tax credit program in the U.S. is the Renewable Electricity Production Tax Credit (PTC), which presently provides companies 2.2 cents per kWh for generation from qualified wind, geothermal, and closed-loop biomass facilities, and 1.1 cents per kWh for other eligible technologies. However, the U.S. experience with this demand pull mechanism has been mixed. Between 1992 when it was enacted and 2007, the PTC has experienced lapses in funding, creating policy uncertainty and significantly affecting the actual adoption of technology. Figure 2-21 illustrates the growth in wind power generation capacity in the U.S. once the PTC took effect, as well as the impacts of the PTC lapses in specific years. (Wiser, Bolinger, & Barbose, 2007)

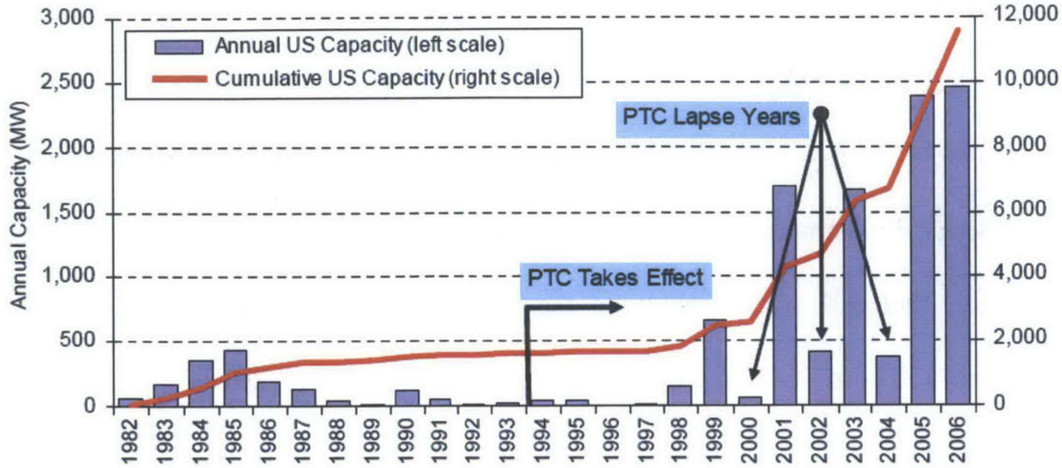


**Figure 2-21 Impact of Production Tax Credit on Wind Power Capacity Growth in the U.S.**
(Wiser, Bolinger, & Barbose, 2007)

Despite the economic incentives provided by demand pull mechanisms, private inventors still do not have sufficient incentive to undertake the level of R&D that is socially optimal. The market failure in this case is that knowledge (the return from R&D) is a public good. From an economic perspective, when a private inventor produces new knowledge, it would like to be able to claim 100% of the returns from that investment. However, when a new technology or invention is developed and sold, part of the new knowledge returns "spillover" into the public domain. From the perspective of other actors, these knowledge spillovers are "free." However, the inventor is uncompensated for the benefits that others receive from this knowledge. . All firms therefore have an incentive to free-ride on the R&D of others, and will themselves under-invest in R&D. A rational agent will invest in R&D only to the point where private returns equal their investment or production costs.

The situation presents a mirror image of the public goods nature of clean-air in environmental markets, and the negative externalities associated with industrial air emissions from the electricity production process. In the absence of environmental policies forcing firms to internalize the negative externality associated with their emissions, firms have an incentive to overproduce emissions because they do not have to pay for them. In effect, they enjoy the benefits of "using up" clean air for free, while the public pays for it (through less clean air). In knowledge markets, the public reaps the rewards of free knowledge, while the inventing firms end up paying for it. Public policies for R&D, therefore, essentially seek to make the public "internalize" the positive externality associated with inventors' knowledge production.

Technology push mechanisms are intended to address this specific market failure and increase the overall success rate of R&D activities. Common direct-support policy mechanisms to achieve this internalization include R&D contracts with private firms, contracts and grants with universities, allocations for research conducted within government labs, and contracts with industry-led consortia or collaborative efforts (such as in the case of the ATS program). Other policy tools support technologies that are closer to commercialization and production, but still focus on technology push. These include mechanisms such as patent protection measures and R&D tax credits.

## 2.3 Long-term Planning Uncertainties

The U.S. electricity generation and innovation systems nexus faces a multitude of uncertainties that the policy maker, business operator, or other stakeholder must grapple with when planning for the system's future. The following section briefly details some of the main uncertainties that mark the long-term expansion planning problem. The first subsection focuses on uncertainties that traditionally have been considered within the planning context, and the second subsection describes relatively new uncertainties that motivate the current dissertation research.

> *"In one word, a key challenge for meeting emissions and technology goals is uncertainty. We are not sure what emissions reductions will ultimately be needed or what the corresponding prices will be. We do not necessarily have a good idea of the costs of large-scale deployment of existing technologies, when breakthrough technologies might arrive, or to what degree costs and quality of existing technologies will be improved. These kinds of uncertainties can create a tension—how to choose among them?" (Fischer, 2009)*

### *2.3.1 "Traditional" Uncertainties*

Uncertainties that long-term electric power system planners have long confronted include uncertainty in demand growth and uncertainty in fuel prices. To meet cost-minimization goals, planners must be able to accurately predict how much electricity will be demanded at a future point in time so that proper amounts and types of new capacity can be added to the system. Too much new capacity and the system will be overbuilt; too little and the system will be unreliable, unable to effectively deliver electricity to consumers upon demand. In recent years, the uncertainty in demand has increased due to increased electricity conservation and efficiency measures consumers can choose (e.g., more efficient home appliances, choices about when to use electricity in areas with time of day pricing), and the possibility of widespread electric vehicle adoption and use. How these choices will impact electricity demand, and how long they will need to take effect are important inputs to the planner's decision making about how to add new generating capacity to the system. Each of these consumer choices can impact the way electricity is demanded throughout a day or a year (the shape of the load curve) and can impact overall demand growth, creating an additional source of complexity and uncertainty.

Fuel prices have also long been a source of uncertainty. As mentioned in Section 2.1, coal prices have historically been low and stable, but natural gas prices have been quite volatile throughout history (Figure 2-22), making it difficult to know a priori whether adding new natural gas-fired generating facilities should be part of a long-term least-cost management plan. As discussed above, the rejuvenation of the domestic natural gas industry due to abundant recoverable shale gas in the U.S. might reduce this uncertainty for the near future, but in the long run, fuel price uncertainty will continue to exist.

Uncertainty in the availability of adequate supporting infrastructure (transmission and distribution lines) is a third key uncertainty in the long-term planning of generating facilities.

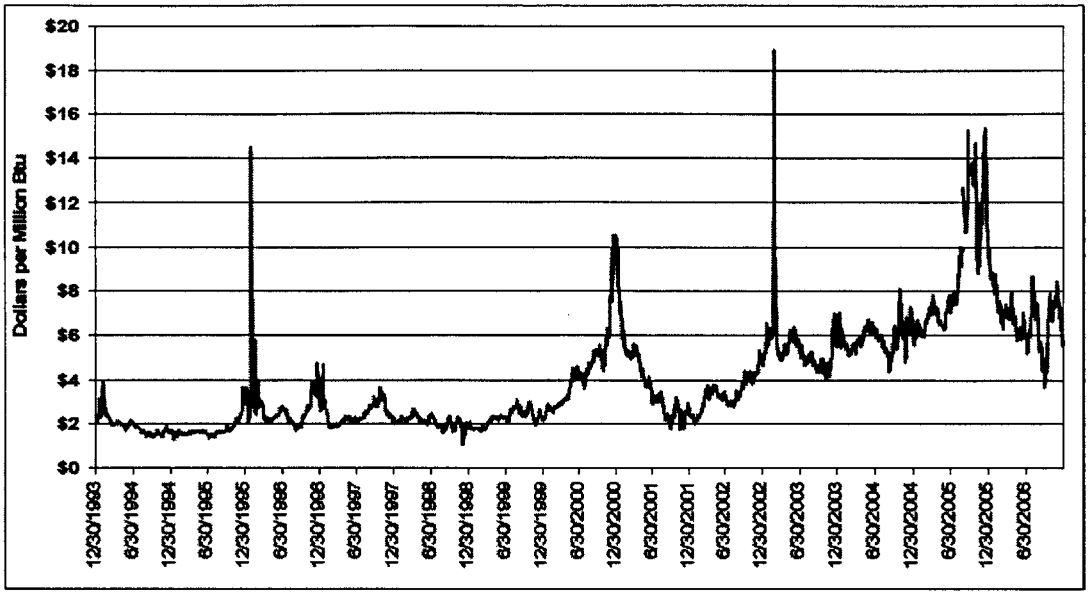


**Figure 2-22 Henry Hub Daily Spot Market Natural Gas Price 1993-2006**
(EIA, 2007b, Original Source: NGI's Daily Gas Price Index, *Intelligent Press*)

### *2.3.2 "New" Uncertainties*

Recent environmental and climate change concerns create additional uncertainties. These include uncertainty in the cost of future technologies to aid in $CO_2$ emission reduction from generation (e.g., carbon capture, storage, and sequestration, next-generation nuclear), the outcomes of R&D investment efforts to invent and bring new technologies to the marketplace, uncertainty in future policies (environmental constraints, regulations, and incentives), and uncertainty and variability in the energy resource availability for certain key renewable energies such as wind and solar.

The uncertainty in the technological change process is inherent. Past research program outcomes can lend some evidence for the quantity and quality of returns to R&D investments, but it is not possible to know with perfect foresight the degree to which innovative efforts will succeed or fail. The innovation and R&D process is by nature stochastic, and thus best described by a probability distribution of outcomes to specified levels of R&D effort (Mansfield, 1968; Evenson & Kislev, 1975). Moreover, these probability distributions are often highly skewed. The majority of outcomes are smaller, more incremental, and less individually valuable contributions to overall technological change, with few occurrences of high value, breakthrough-type innovations (Jaffe & Trajtenberg, 2002; Pakes, 1986). The shape of these distributions can also be quite different for various technology groups within the same industry. Though still skewed, distribution profiles characterizing technologies that seem to experience "slow and steady progress," across different levels of R&D co-exist with profiles for technologies that fall into a more "high-risk, high-reward" type of innovation process (Chapter 6). Likewise, the nature of learning-by-doing is uncertain; human experience with other technology types and resulting learning rates and cost reductions can provide evidence of what to expect, but this cannot be known a priori due to the inherent differences in how people and organizations learn.

As mentioned in Sections 2.1 and 2.2, the past decade has seen discussion about federal climate policy and pricing carbon, but at present no national economy-wide legislation has been enacted. Political issues and competing interests have made it difficult to pass such legislation. Economic recessions, strong support for other domestic policy agenda items such as finance or healthcare, and even the historically low natural gas prices have all helped to shift the focus away from climate policy and greenhouse gas emissions mitigation in recent years. These ups and downs create a sense of uncertainty about the likelihood of future mandatory climate change regulation, which greatly influences the way long-term planning in the electricity industry is performed. Shorter-term policy uncertainties are also prevalent in the system, as shown in the case of the U.S. Renewable Electricity Production Tax Credit (PTC) program, where lapses in the program caused the industry to quickly and substantially change its capital investment pattern.

Finally, energy from natural resources such as the sun, wind, rivers, and other hydro reservoirs, retain an inherent natural variability that the long-term electricity planner must account for in building a reliable and efficient power system. Averaged out over the course of a year for example, wind or solar power might convert about thirty percent of its energy into usable electricity to meet demand. However, within the year, from season to season and day to day, the amount of wind or sun available to generate electricity is quite variable. Figure 2-23 shows the highly volatile output from a single wind turbine in Germany (blue line), compared to the spatially averaged output when groups of turbines are considered, or wind power across the entire country. Note the continued volatility even in the output when the entire country is considered. Despite the most sophisticated forecasts, the amount of variability is not entirely predictable. This intermittency must be accounted for in long-term plans by making specific decisions about the location and type of balancing resources, such that this low-cost, low-carbon resource can be efficiently used, but in a manner that does not adversely affect electricity reliability.

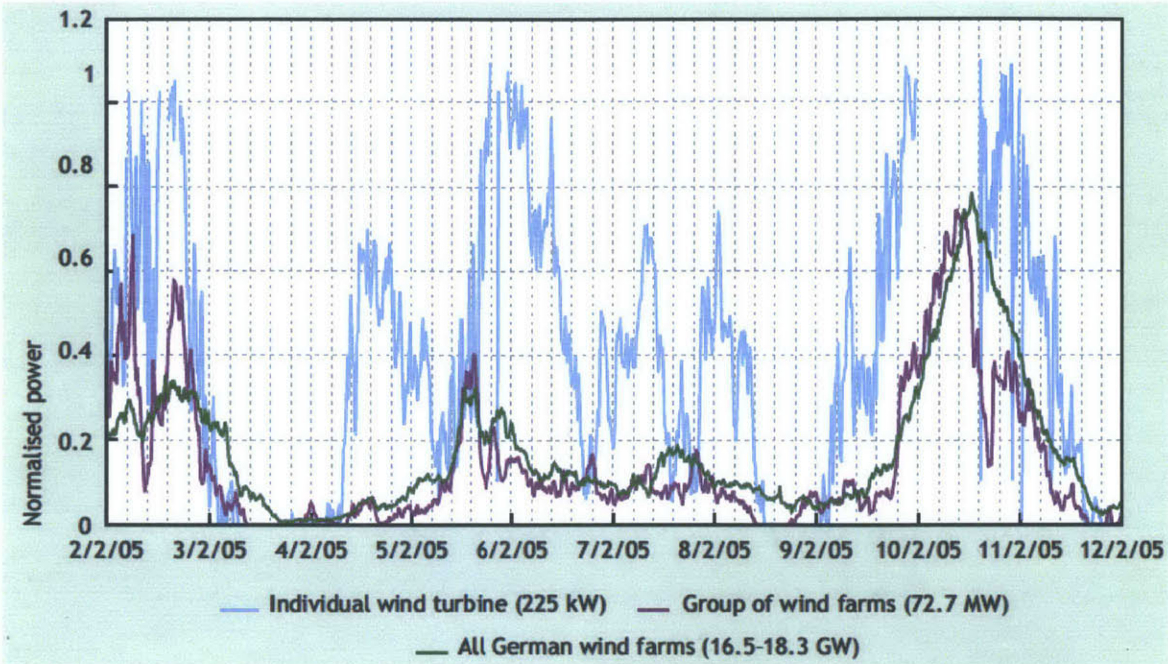


**Figure 2-23 Volatility in Wind Turbine Output, Germany** © OECD/IEA (IEA, 2008)

The next chapter reviews the literature on state-of-the-art electricity capacity expansion planning tools with respect to representation of power system details, technological change, and uncertainty.

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# Chapter 3 Literature Review

There are many challenges to representing critical features of the long-term electricity generation capacity planning problem in a model that can inform the policy process. At present, national-scale electricity generation capacity expansion models can evaluate several aspects of the interaction between environmental policies and the power industry, but ultimately lack one or more of three overarching features jointly necessary to provide useful insights about an optimal balance between R&D program and power plant investments. First, they lack resolution of the critical structure of the electricity sector. Second, they lack an explicit endogenous representation of the effects of learning-by-searching technological change. Third, they lack an efficient decision-analytic framework to explore R&D and plant investment options under a range of uncertain technology futures. This chapter reviews details about the current capabilities of state-of-the-art electricity capacity expansion models with respect to their representations of power system details, technological change, and uncertainty, and thus their effectiveness for decision support within this context.

## 3.1 Resolution of the Structure of the Electric Power Sector

The majority of models used to inform policy tend to be lacking in technological explicitness, macroeconomic completeness, or microeconomic "realism," (Bataille, Maccard, Nyboer, & Rivers, 2006). Two types of models currently dominate in the spectrum of tools to help policy makers understand the implications of their decisions on businesses and consumers: 1) economic models that represent the macroeconomic implications of certain policies, but typically omit key engineering constraints that influence firm-level decisions and the technology mix that would result, and 2) engineering-cost models that are designed to represent rich technological detail, but do not explicitly capture firm-level decisions on technology adoption or macroeconomic behaviors and feedbacks. This discordance has driven an entire movement in hybrid energy policy modeling, which aims to link engineering cost models with economic models in order to capture the spectrum of needs to inform policy. However, many challenges remain for hybrid models to represent the full range of processes and feedbacks relevant to the policy discussions they are intended to inform.

### *3.1.1 Economic Models*

Many existing models for environmental and climate policy analysis focus on representing the economy as a whole, and for tractability reasons use highly simplified representations of the electric power sector. Classified by some as "top-down" environment-economy models, they can be broadly categorized into one of two groups: computable general equilibrium models (CGEs) or inter-temporal optimizing growth models (Sanstad & Greening, 1998).

Aggregate energy-environment CGEs such as the MIT Emission Prediction and Policy Analysis (EPPA) model or the EPA Applied Dynamic Analysis of the Global Economy (ADAGE) model are two examples (Paltsev et al., 2005; Ross, 2008). These models represent multiple regions and multiple industries. Productive output is the result of demand and supply of multiple sectors of the economy being in equilibrium, determined by the simultaneous clearance of all represented markets. The strength of these models is that they capture important economic feedbacks between sectors of the economy, such as substitution or trade effects. They are particularly useful for describing how price changes in one sector affect all other represented sectors of the economy.

However, these economic models typically lack detail about technology types, operational constraints, and important dynamics of the sectors and industries they represent. Considering the electric power system, this does not allow for generation technology expansion decisions to be made in a manner consistent with how different technologies within the system complement and interact with each other. Computable general equilibrium models typically use nested CES (constant elasticity of substitution) functions to represent how fossil-fuel and other primary inputs are converted into electricity. Through the CES structure, input factors are used in proportion to their marginal productivity and can be substituted for other inputs if relative prices change. More importantly, relative costs of technologies in CGE models are often calibrated to exogenously determined "Levelized Costs of Electricity (LCOE)," values, which depend on assumed capacity factors. Use of capacity factors can be limiting because they assume that the physical operation (how much electricity each plant type generates) of these technologies can be known before witnessing the level of electricity demand or energy prices entering the equations. Additional operational constraints of the physical electricity system, such as its capability to handle intermittent renewable power generation, transmission congestion, and resource availability rates, are implicit within these relative costs. While these economic representations are often established on theoretical and engineering grounds, and the decision to choose macroeconomic completeness over technological explicitness is knowingly made, such models are not appropriate for rigorous sector-level investigations about optimal investment decision making across different technologies. They simply lack the technological detail and operational realism that exists within the electricity system to make the serious inquiry.

Most intertemporal optimizing growth models widely used for energy and environmental policy analysis, such as the Dynamic Integrated model of Climate and the Economy (DICE) (and its extensions such as RICE and ENTICE), are built upon the theoretical Ramsey neoclassical optimal growth framework. In the Ramsey model, growth is driven by capital accumulation and economic equilibrium is reached when the representative agent's utility function is optimized intertemporally (Nordhaus, 1994; Nordhaus, 2010; Popp, 2004; Popp, 2006). To keep these models tractable, the economy is typically represented through a single or very few aggregated sectors and production of a single final good; details about the productive inputs are also limited (e.g., capital, labor, and energy). This framework therefore necessarily constrains inquiries about interactions between technologies within a sector.

### *3.1.2 Engineering-Cost Models*

In contrast to economic models, engineering cost-based models (also called "bottom-up" models by some research communities), are built upon engineering principles and represent detailed technical characteristics of the industries or technologies within the sector(s) included. Keeping these models tractable usually requires a partial-equilibrium perspective, rather than explicit representations and interactions between each sector and the rest of the economy, but their ability to study the technical interactions within the energy sector is strong. These models can vary in their structure and solution approach, but most use a dynamic linear-programming or mixed-integer programming optimization framework, or a simulation framework such as business dynamics or agent-based modeling (Azar & Dowlatabadi, 1999).

Technology-rich engineering-cost models such as the National Renewable Energy Laboratory's ReEDS (Regional Energy Deployment System) model, the MARKAL modeling framework originally developed by Brookhaven National Laboratory (and its several variants), the International Institute for Applied Systems Analysis (IIASA) MESSAGE model, Research Triangle Institute International's (RTIs) Electricity Markets Analysis (EMA) model, the U.S. Environmental Protection Agency's (EPA) Integrated Planning Model (IPM), and the electricity capacity planning module of the Energy Information Administration's (EIAs) National Energy Modeling System (NEMS) are some of the most widely-known and used optimization models for electricity and environmental policy analysis (Short et al., 2009; Loulou, Goldstein, & Noble, 2004; Messner, 1997; Ross, 2008; EPA, 2010; EIA, 2009a). Each of these models is designed to conduct analyses specific to the energy sector (and in many cases specific to the electricity sector), capturing multiple regions, multiple time periods, and several different types of technologies and their characteristics (typically 20 or more electricity generation technology types).

The objective of these models is generally to determine the least-cost method of operating existing generation equipment and/or building new equipment to meet growing electricity demand on a seasonal and time-of-day basis, subject to several operational constraints. These constraints vary according to the purpose of and level of detail in the models, but often include constraints such as the availability and quality of renewable resources, access to and costs of transmission, ancillary service requirements and their costs, and physical limitations of operating different types of power plants (Short et al., 2009). A key feature of engineering-cost models distinct from the economic models is the lack of assumption about fixed operation of the generating equipment. Whereas economic models assume capacity factors for the different technologies, engineering-cost models through their detailed representations of technology cost structures (e.g., investment costs, other fixed costs, fuel costs, other variable costs), and time-of-day electricity demand, allow generator operation decisions to be determined through the optimization. Thus, the capacity factor of each technology is calculated as an output of the model. This feature allows for the interaction and complementarity of the different technologies within the system to be explicitly and more realistically considered. For the purposes of investment planning within the electricity sector then, use of engineering-cost models provides for resolution of the critical physical structure of the system components.

### *3.1.3 Hybrid Models*

Finally, realizing the relative strengths and weaknesses of either the economic modeling or engineering-cost modeling approach, and desire to study energy and environmental policy decisions from both a rich technological and complete macroeconomic perspective, hybrid modeling has risen in popularity over the past ten to fifteen years. These models aim to link engineering-cost and economic models in order to capture the full range of specifications needed to inform policy. However, these efforts have been met with varying degrees of success, and many challenges remain for hybrid models to represent the full range of processes and feedbacks relevant to the policy decisions they intend to inform.

Two popular models that fall in the hybrid modeling category are the Model for Evaluating the Regional and Global Effects of GHG reduction policies (MERGE) of Mann, Mendelsohn, and Richels (1995) and the World Induced Technical Change Hybrid Model (WITCH) (Bosetti et al., 2006). At its core, MERGE retains an economic intertemporal optimizing growth structure akin to the DICE model, but disaggregates productive energy inputs into electricity and non-electricity sectors, as well as the electricity sector into a small number of different technology types. However, the model remains limited in representing the actual structure of the electricity generation supply sector by omitting critical information about the detailed cost structures of the different technologies and details about the temporal variability of electricity demand. Likewise, the WITCH model also retains a relatively economic perspective. It focuses on disaggregating the energy sector, but continues to use a traditional CGE nested CES structure to represent the substitutability between different types of electricity technologies in producing electricity, and typical capacity factors, or "plant utilization rates," which make critical assumptions about their operations. Therefore, while hybrid modeling is moving in the right direction, overall these models still lack the necessary structure for rigorous study about investment planning in the electricity sector.

## 3.2 Representation of Technological Change

Costs of electricity generation technologies have decreased over time (Figure 3-1), while efficiencies and other performance attributes have improved. Following this, during the past fifteen years the quantitative energy and environmental policy analysis modeling community has made efforts to represent the process of technology improvement within their analyses. However, the type of technological change represented and how specifically it is incorporated varies greatly from framework to framework and model to model. The following section provides a review of the main pathways for representing technological change in models for energy and environmental policy analysis. As discussed in more detail below, whether a model is structured for economic analyses or engineering-cost analyses appears to drive the specific mechanism used to represent technological change.

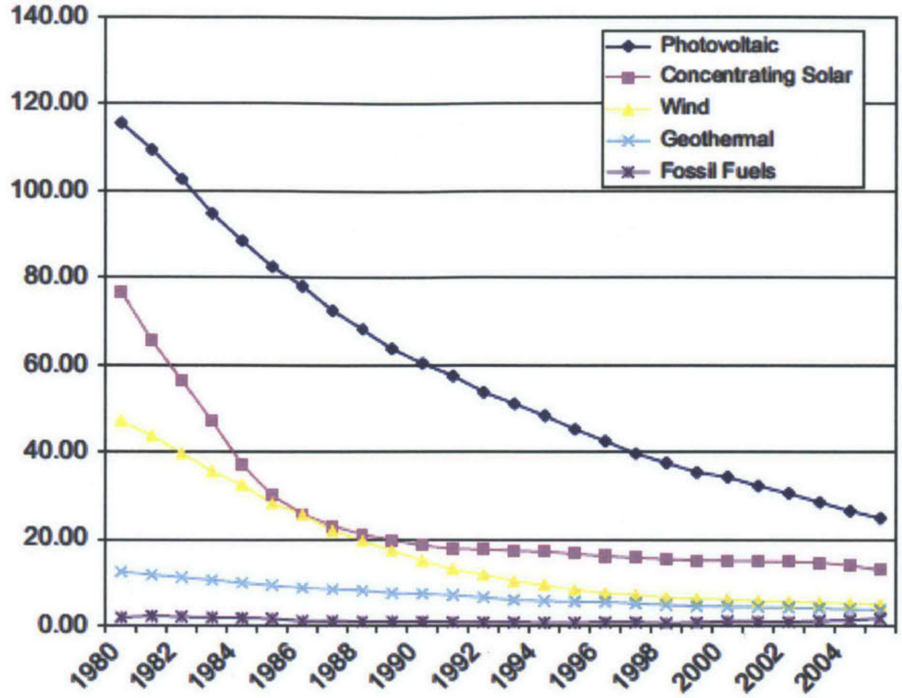


**Figure 3-1 Technology Costs for Various Electricity Generation Technologies, in cents per kWh**[2]
(Schilling & Esmundo, 2009; original data from NREL and US DOE)

### *3.2.1 Exogenous Technological Change*

The traditional approach to incorporating technological change within models for energy and environmental policy analysis is to use an exogenous assumption about future reductions in technology investment costs, availability of new technology, or improvements to energy efficiency. These are often referred to as "technology snapshots" (Edmonds, Roop, & Scott, 2000). This is done through the use of fixed, empirically-derived time-trends, which represent how technology improves as a function of time. Economic CGE models such as the MIT EPPA model or the EPA ADAGE model use an "autonomous energy efficiency improvement (AEEI)" parameter to model

[2] Includes capital, O&M and fuel costs; fossil fuel costs include only fuel costs due to unavailability of capital costs prior to 1990

technology improvement over time (Paltsev et al., 2005; Ross, 2008). Calibrated to historically observed energy consumption trends relative to GDP and prices, the AEEI parameter is used to model expected changes in energy consumption per unit of output. The early approaches to exogenous technological change in intertemporal optimizing growth models such as DICE consists of aggregating all technological change within a single, exogenously decreasing total factor productivity scaling parameter within the production function for economic output (Nordhaus, 1994). In engineering-cost energy and electricity systems models such as the NREL ReEDS model, or the RTI Electricity Markets Analysis (EMA) model, the approach typically uses an exogenous discrete time trend for the costs for different technology categories (Short et al., 2009; Ross, 2008; Grubb, Kohler, & Anderson, 2002). For example, in the ReEDS model, capital costs decline between decision periods and heat rates (power plant efficiencies) improve.

Overall, use of such exogenous assumptions about the rate of technology improvement in these models does not preclude meaningful interpretation for real-world technological change, but does limit the opportunity for specific types of inquiries. First, the majority of models utilizing exogenous technological change assumptions consider a single technological change parameter or mechanism, which aggregates the many different pathways from which that technological change may have occurred—through experience, explicit R&D, spillovers from another industry or sector, or simply the general rate of technological change of the entire economy. This aggregated technological change approach limits the ability to study the contribution of individual pathways on the final objective (e.g., through sensitivity analyses). Second, and perhaps more importantly for energy investment planning, such exogenous representations do not allow decision makers to evaluate the true impacts of policies and current decisions on the future state of the system (e.g., generation technology mix, technology costs) because technology characteristics in the model do not respond to changes in R&D or past capital investment decisions (Clarke, Weyant, & Edmonds, 2008; Clarke, Weyant, & Birky, 2006).

### *3.2.2 Endogenous Learning-by-Doing Technological Change*

In an effort to overcome this limitation, models began including various endogenous representations of technological change. The simplest approach consisted of endogenous "learning-by-doing (LBD)" curves (also known as experience curves), which represented how technologies improved as a function of cumulative production or use. In the case of the electric power sector, this extended to cumulative installed capacities of different technology categories, or cumulative electricity production from that technology (Clarke et al., 2008). LBD formulations are founded upon the concept that technology improves (e.g., costs decline) as cumulative experience with the technology increases; repetition and familiarity breeds efficiency. Steady progress on the empirical research side in gathering and statistically analyzing time-series data on cumulative installed capacities and technology costs have been especially useful for calibrating endogenous technological change dynamics within formal models (e.g., Ibenholt, 2002; Colpier & Cornland, 2002; Yeh & Rubin, 2007).

The earliest use of endogenous LBD in a engineering-cost energy systems model focused on the power sector is seen in IIASA's MESSAGE model, and since then it has been applied in a range of other models to the point where at present inclusion of some form of LBD is the norm (Messer, 1997). For example, learning-by-doing pathways are also present in the engineering-based MARKAL, EIA NEMS model, the global GENIE model of power generation of Mattheson and Wene (1997), and the IIASA Energy Research and Investment Strategy (ERIS) model that focuses on the power generation sector. In each of these cases, the specific investment costs for the technologies is affected by experience with the technology (Loulou, Goldstein, & Noble, 2004; EIA, 2009a; Seebregts et al., 1999; Morris, 2002; Mattsson & Wene, 1997; Berglund & Soderholm, 2006; Kypreos & Barreto, 2000).

Most of the focus on endogenizing technological change in economic models has been on R&D and "learning-by-searching" (discussed in detail below), although van der Zwaan et al. (2002) provides an example of including endogenous LBD in their energy-environment model, DEMETER (the Decarbonization Model with Endogenous Technologies for Emission Reduction). In terms of considering endogenous LBD in hybrid models of energy and environment, in a version of the original MERGE model called MERGE-ETL, endogenous technological learning is applied to several electric and non-electric sector technologies. The formulation for the experience curve is identical to those used in engineering-cost models, with cumulative installed capacity of the technologies affecting the specific investment costs in future decision periods (Kypreos & Bahn, 2003).

Endogenous LBD representing how technology improves as a function of cumulative installed capacity or cumulative use, are certainly a major improvement compared to exogenous time-trends. However, this approach also has some limitations. First, each of these applications is essentially using cumulative capacity or production as a proxy for the knowledge accumulation that drives technology improvement (e.g., investment cost reductions), which asserts that all (or almost all if an exogenous rate is also used) technological change results from activities that respond to changes in technology deployment or demand. However, this may or may not include other important sources of technological change such as R&D (Clarke et al., 2008). Following on this, use of these single-factor LBD curves, also assumes that technological change is relatively "free." Although investment costs exist, accounting for the opportunity cost of the resources uses to improve the technology is omitted. Second, while NEMS, MESSAGE and other models with single-factor LBD curves implicitly account for the technology improvement that results as a function of R&D, this formulation of endogenous technological change still limits the ability to explicitly study how R&D investments affect technology improvement because technology costs are unresponsive to changes in R&D. The second of these limitations directly affects the goal of the current dissertation, as R&D investment decisions are considered a major pathway for technological change.

### *3.2.3 Endogenous Learning-by-Searching Technological Change*

Appreciating the importance of including explicit R&D-based technological change, a number of models have incorporated endogenous "learning-by-searching (LBS)" formulations. These efforts are often supported by empirical studies that link cost reduction to R&D investments (e.g., Schilling & Esmundo, 2009). However, recognizing that by using R&D investment data as an input, most conventional learning-by-searching curve analyses are likely missing important private sector technology developments, other empirical studies detail the effect of public and private R&D effort on technological change. One method of doing so while still retaining disaggregated technology data is through the use of patent citation data, as discussed by Jaffe and Trajtenberg (2002) and Griliches (2009), and seen in the econometric analyses of Popp (2002) and Popp (2005). Another method is through the use of expert elicitation, where knowledge experts in relevant technology fields provide guidance and estimates about the pace of future technological change (e.g., Baker et al., 2009; Gallagher et al., 2011). While each of these methods face inherent challenges in incorporating results into formal models of energy and environment, they have proven useful in beginning to calibrate more detailed technological change pathways into numerical models (Clarke et al., 2008; Popp, 2005).

In addition, a number of models have endogenized learning through the use of "two-factor" learning curves, which explicitly account for learning through both cumulative experience (LBD) and cumulative R&D effort (LBS). Recent empirical studies that have developed two-factor technology learning curves, which consider the effect of both capacity and R&D investments on costs, have been particularly useful for these more integrative models (e.g., Klassen et al., 2005; Soderholm & Klassen, 2006; Jamasb, 2007; Kobos et al., 2006).

Most of the early work to include LBS technological change within quantitative models for environmental and energy policy analysis took place within an economic framework (van der Zwaan et al., 2002; Popp, Newell, & Jaffe, 2009). Goulder and Scheider (1999) incorporate R&D-based learning-by-searching in a research-scale analytical and numerical CGE climate-economy model to test the effect of incorporating LBS on climate change policy. As is the case with many other present day economic models that include LBS technological change, LBS is modeled through the use of an accumulating knowledge capital stock, which is increased via R&D investments, and is either incorporated directly into the production function(s) or cost function(s), depending on the structure of the model. The approach for endogenous LBS in the ETC-RICE model, a regional version of original global DICE intertemporal optimizing growth climate policy model is similar (Buonanno et al., 2003). In this model, endogenous technological change affects total factor productivity through addition of an accumulating knowledge stock into the production function, which is related to R&D investment decisions. The knowledge stock also affects the emissions-output ratio (decreasing emissions per unit output). Also from an economic perspective, Goulder and Mathai (2000) incorporate LBS within a cost-function-based climate policy model for intertemporally choosing emissions abatement and R&D investments to minimize total costs (of emissions abatement and R&D investments) of meeting a specified emissions target. In this model, the LBS pathway affects the abatement cost function through an R&D-based accumulating knowledge capital stock.

Finally, Popp (2004) and Popp (2006) incorporate endogenous LBS technological change into the DICE model, developing the ENTICE and ENTICE-BR models for climate policy. In ENTICE, endogenous LBS technological change increases the stock of energy-related human capital (the cumulative knowledge stock), which can substitute for carbon-based fossil fuels to produce energy within a CES function. In this framework, technological change represents improvements to energy efficiency that substitutes for fossil fuels; as cumulative knowledge increases, there is a shift away from fossil-fuel energy use, and therefore a reduction in emissions (Popp, 2004). ENTICE-BR adds a carbon-free backstop energy technology to the mix of technologies available to meet total energy production, retaining the original ENTICE structure of endogenous LBS technological change for energy efficiency, but introducing LBS technological change for the backstop through a single-factor learning curve concept. In this formulation, the simultaneously accumulating backstop human capital knowledge stock affects the price of the carbon-free backstop technology, allowing energy-use to shift towards it and away from fossil-fuels in a nested CES structure (Popp, 2006). A key feature of the ENTICE and ENTICE-BR models that is not seen across many other numerical climate-energy models but is valuable for understanding and being able to study in more detail the drivers of LBS technological change, is the use of a two-factor production function for linking the knowledge stock to R&D investments. In the other models reviewed, knowledge stock typically depends linearly on R&D investments. Building upon the formulation proposed by Jones (1995), and seeking to calibrate the models to real-world data and build upon empirical evidence that the state of scientific knowledge affects the overall outcome of R&D investment, the ENTICE and ENTICE-BR models utilize two-factor production functions for the creation of new knowledge through "innovation possibilities frontiers" (IPFs). The two factors in the IPF are R&D investments and the cumulative knowledge stock, and new knowledge then accumulates into the knowledge stock.

As hybrid modeling is still emerging as an overall concept and modeling framework, there has been relatively sparse effort on introducing endogenous LBS technological change within these models. One example is the WITCH model, where technological change is endogenous and driven by both LBD and LBS (Bosetti et al., 2006). However, their formulations are separate and therefore relatively limiting: the endogenous LBD pathway affects costs in the power generation industry included in the model, while LBS affects energy efficiency and the cost of non-electricity technologies (i.e., advanced biofuels). Energy efficiency improvements are formulated through the use of an innovation possibilities frontier and nested CES structure employing the method used by Popp (2004); advanced biofuels cost reductions are formulated using a modified single-factor learning curve concept (Carraro, 2009). Overall, while there has been significant effort to incorporate LBS technological change into models for environmental and energy policy analysis, the WITCH model case is a good example that the critical feature that many of these efforts lack is a combined treatment of endogenous LBS and LBD technological change with good resolution of the electric power sector's structure.

### *3.2.4 Endogenous Learning-by-Searching and Learning-by-Doing Technological Change*

The frontier of research in this respect is to develop engineering-cost energy systems models that endogenize technological change through learning-by-doing *and* learning-by-searching. Compared to the multitude of models available for energy systems and environmental policy analysis present, only a few have moved in this direction. Those that have are able to capture critical power system details as well as represent the effect of R&D investments and cumulative experience on technological change.

The extended energy-systems ERIS model is an example of a model at this frontier (Turton & Barreto, 2004; Barreto & Kypreos, 2004; Miketa & Schrattenholzer, 2004). ERIS is an engineering cost-based electricity generation capacity and R&D

investment planning (optimization) model, the extended version of which has incorporated a two-factor learning curve that manages technology investment cost reductions as a function of both R&D investments and cumulative installed capacity. Additionally, because LBD and LBS are both explicitly included in the model, sensitivity of optimal plans to the specific learning pathways can be tested, as shown in Miketa and Schrattenholzer (2004).

A modified version of the POLES world energy systems model with LBD and LBS pathways for simultaneously reducing the specific technology investment costs is another example (Kouvaritakis et al., 2000). Finally, in a study to assess the effectiveness of different environmental and technology policy mechanisms for carbon emissions reduction in the energy sector, Fischer and Newell (2008) develop a stylized partial-equilibrium economic model of the U.S. electricity generation industry incorporating both endogenous LBD and LBS for the non-emitting emerging renewable resource technology. In their formulation, the knowledge stock generated is a function of both cumulative knowledge from R&D investments and cumulative experience (output). However, the purpose of their inquiry necessitated representing a profit maximizing generation sector, a knowledge market, and an actual electricity market which created dimensionality challenges that subsequently required using highly stylized generation expansion equations and very low resolution in technology categories and decision periods. Thus, the technological explicitness and engineering cost-based nature of their model was relatively compromised.

### *3.2.5 Opportunities for Research*

Engineering cost-based energy-systems planning models that include explicit LBD and LBS representations are the state of the art with respect to numerical energy and environmental models capable of studying optimal R&D and capital investment strategies for the electric power sector. However, this area of research is still emerging and there are many opportunities for contribution through use of alternate formulations for the learning pathways, and improvement in the structure of the models (Clarke et al., 2008; Barreto & Kypreos, 2004).

Another limitation of current approaches is that representations of LBS technological change and the underlying human capital knowledge stocks that drive it are often represented as linear functions of R&D investments. This formulation is usually a conscious decision on the part of the modeler(s) due to the data limitations of calibrating a different functional form. However, this formulation limits the interpretation of the R&D pathway to public R&D activity (private R&D data is not readily available at the level of detail needed to support engineering-cost modeling), and also limits the opportunity to study effects of the different drivers of accumulating scientific knowledge for a technology (Rennings & Voigt, 2008). More explicit modeling of the process of new knowledge creation through use of an innovation possibilities frontier resembling Popp (2004), but within the context of an engineering-cost energy systems model would be valuable, particularly given the empirical support for doing so.

With respect to the treatment of LBS and cumulative knowledge stock formulations for different technology groups, although multiple technologies are considered within engineering-cost energy systems models, the modeling community often uses similar or identical assumptions for learning-related parameters across the different technologies, citing lack of empirical support for doing otherwise. For example, Miketa and Schrattenholzer (2004) use the same learning rate for both wind and solar technologies in determining the optimal allocation of R&D funds to the two electricity technologies in the extended version of ERIS. Another common parameter assumption includes utilizing the same rate for the depreciation of the knowledge capital stock over time for different technologies.

Finally, as described below, there still remains a general lack of consideration for uncertainty in technological change across many existing models used for energy systems R&D and capital investment planning, and several authors of the models reviewed above have called for the need to do so (e.g., Barreto & Kypreos, 2004). With exception to the models reviewed below, the majority of models still use frameworks structured for deterministic (perfect foresight) analysis. However, the outcomes to R&D investment are inherently uncertain, and investment strategies need to be flexible and adaptive to the nature of the R&D and technological change process. The outcomes to R&D are not only uncertain, and thus best represented by probability distributions, but the distributions are usually highly skewed. Both the theoretical and empirical literature have shown the skewness of returns to R&D (Jaffe & Trajtenberg, 2002; Pakes, 1986; Scherer & Harhoff, 2000). There is an opportunity to contribute to the energy and environmental modeling community by helping to further develop this next generation of stochastic investment planning tools.

## 3.3 Decision Making Under Uncertainty

This section describes the state of research with respect to integrating uncertainty into energy and environment planning models. Due to the extremely broad research area, the focus of this review will be on applications within the energy industry and electricity sector, and on methods for integrating uncertainty about technological change within models used for R&D and/or energy capital investment planning. However, as discussed in Chapter 2, there are several different uncertainties that must be addressed when making investment planning decisions. Many of these uncertainties have been integrated into decision support models in some form or another for different types of analyses and from which lessons can be drawn. Overall, it can be concluded though that there is extensive opportunity for improvement in integrating uncertainty within electricity R&D and capital investment decision models. Further, there is opportunity to integrate the three features of 1) detailed resolution of the electric power sector; 2) representation of endogenous LBD and LBS technological change; and 3) capability to make decisions under uncertainty into a single framework.

### *3.3.1 Deterministic Modeling Efforts*

The main methods used to structure numerical decision support models for the electric power sector generally are generally classified as either optimization models or simulation models. For deterministic analyses, the main optimization methods include search techniques, linear programming (LP) models, mixed-integer programming (MIP) models, dynamic programming (DP) models, and other decomposition techniques. Optimization methods have traditionally been the dominant choice of the electricity industry. Across these techniques, the level of detail and sub-sectors within the power system included in the model can vary widely, but the overall objective is usually to find the cost-minimizing long-term generation operation and expansion plan, subject to model constraints (e.g., meeting electricity demand at a minimum level of reliability). The earliest and simplest models for long-term electricity generation expansion planning under perfect foresight were either LP or DP models (Turvey & Anderson, 1977; Petersen, 1973; Poch & Jenkins, 1990; Hobbs, 1995). LP models have the benefit of very efficient solution algorithms, easily embedded constraints, and single solutions. However, they are limited by the fact that they apply only to continuous variables where the objective function and all constraints are necessarily linear. Mixed-integer programming (MIP) addresses this problem by allowing integer variables (e.g., discrete power plants can be represented), but computation times are increased. DP methods allowed for more flexible objective functions and similarly easy inclusion of discrete variables as decision variables, but computation times can also be limiting.

More recently, simulation techniques have been applied for electricity generation planning and mainly consist of system (business) dynamics, agent-based modeling, or other game theoretic models. System dynamics is based on control-theory concepts. The structure and interactions between different components within the system being studied are represented using differential equations that describe behaviors and links. Explicit recognition of feedback and time lags are the hallmark of system dynamics, and as such it has been a particularly useful tool in power system planning when the purpose of inquiry concerns the behavior of system agents or evolution of the system. On the downside, system dynamics has been criticized in the power system planning community for not being as controlled and transparent a method relative to others (Sanchez et al., 2012).

Agent-based modeling has proven useful in modeling electricity industry activities. However, overall, it has been more easily applied to shorter-term behaviors such as generation companies' bidding strategy decisions when considering operation of their existing plants, rather than long-range expansion planning decisions (Hernaez, 2008; Sanchez, 2008).

Finally, game theoretic models are abundant in the modern generation expansion planning literature. Games are solved using different mathematical programming techniques such as iteration, or as mixed complementarity problems. Overall, games provide a mechanism for studying markets and competition between firms, which is particularly useful in deregulated market frameworks, but like agent-based models, they have been used mostly for short-term generation planning activities such as operational decisions and bidding strategy planning, due to their dynamic character. Dynamic games would be useful for long-range planning, but the number of agents these models can handle is limited, which creates a problem for electricity generation expansion planning that needs to consider several players over long time horizons. Still, several studies have provided good examples of the application of game theoretic models to electricity generation expansion planning. Haikel (2009) applies game methods to study the efficiency of various capacity-based incentive mechanisms for ensuring capacity adequacy in electricity markets, and Murphy and Smeers (2005) illustrate game methods that can be applied to study capacity expansion in imperfectly competitive restructured markets.

### *3.3.2 Stochastic Modeling Efforts*

During the past twenty years, there has been a gradual shift towards considering uncertainty and developing stochastic optimization models in the electric power industry. This was driven first mainly by deregulation of power markets in which the predictability of power purchases was reduced (Spangardt et al., 2006). Decision makers required methods to determine the best hedging strategies against unpredictable situations, and plans that considered the risk characteristics of the environments in which they operated.

At present, stochastic applications for the generation sector consider a range of time scales. Short term planning, which occurs on the order of a week and involves scheduling generation resources to generate power in advance (i.e., unit commitment), and planning electricity trades in the market, require stochastic models to account for the uncertainty in the electricity demand forecast and renewable resource variability (Ramos et al., n.d.). Medium-term planning, which covers approximately three months to two years out involves optimizing the purchase of power based on expected sales, and as such requires a stochastic approach to consider variability in the financial power market, or the allocation of hydro resources over different seasons. Finally, relevant to the current research, long-term generation expansion planning, which typically covers anywhere from five to 50 years out, involves decision making about investments for new generation capital assets (i.e., power plants). Stochastic approaches have been applied in the long-term expansion planning context because the uncertainties present at the shorter time scales tend to persist (and actually increase due to the longer planning horizon), and additional uncertainties such as technological change and environmental and other regulatory changes should also be considered (Spangardt et al., 2006).

The range of approaches to considering uncertainty and stochastic processes within long-term generation planning has been quite varied. A common approach still in practice today is the use of sensitivity analysis, scenario analysis, or Monte Carlo-based simulation with deterministically structured models. Bergerson and Lave (2007) use a sensitivity analysis approach to study coal fired power plant investment decisions under uncertain carbon legislation and technological uncertainties for advanced coal fired plants. The approach uses an engineering-cost structure and varies parameters representing these features to determine the optimal decisions for each possible realization of legislation or technology path. Scenario analysis and Monte Carlo simulation are similar to sensitivity analysis approaches, but grow out of their more formal counterpart literatures. Scenario planning is a method used to develop alternate, plausible futures, and a description of the types of changes that would occur to exogenous variables of interest to the decision maker (Wack, 1985). It creates a means for understanding and evaluating policy decisions through informed ideas of the future (Schwartz, 1991). An example of the use of scenario analysis in the context of electricity generation planning and numerical modeling is seen in Richels and Blanford (2008), who study the role of technological change in managing total system costs of meeting a carbon target for the U.S. In their study, two alternate portfolios of technologies and technological change are analyzed, one that represents modest investment in clean electricity technology and one that represents more aggressive deployment. Monte Carlo-based simulations stem from the probabilistic analysis and statistics literatures, where probability distributions are typically used to characterize uncertain parameters and a statistical sampling method is used to draw values that are then used in the model.

Expected values for the optimal decisions assuming perfect information are then computed across the different Monte Carlo runs, and used as the solution to the stochastic problem. A good example of the use of Monte Carlo-based simulation is seen in Hoyos et al., (n.d). who study the influences of carbon price and fuel price uncertainty on generation expansion planning.

Two final examples using these types of methods with slightly more rigor, but still from within a deterministically structured model, are see in Blanford's (2009) study of R&D investment strategies for the power sector in the face of climate change, and the stochastic work involving the MESSAGE model. Using the MERGE model, Blanford develops and uses a separate stochastic R&D module to help map plausible alternate technological change pathways on the basis of R&D investment decisions to outcomes of the model on an expected value basis (2009). Stochastic versions of the IIASA MESSAGE energy systems model also incorporate uncertainty analysis by introducing expected value-based penalties into the objective cost function to represent the effect of underestimating unpredictable future technology investment costs (Messner et al., 1995; Grubb, 2002; Grubler & Gritsevskii, 1997). Although the details of the methods vary, both of these methods ultimately incorporate uncertainty from an expected value perspective directly into the objective functions of the problem.

The overlap between these three approaches is considerable, but in general the scenario planning method tends to require a deeper understanding of the underlying system than other methods. Additionally, scenario analysis typically uses the fewest number of scenarios across model runs, followed by sensitivity analysis, and then Monte Carlo simulation with the greatest number of model runs. Also, results from sensitivity and scenario analyses tend to be interpreted from a more qualitative perspective, whereas Monte Carlo simulation is more quantitative and final expected value solutions assuming perfect foresight are often provided. While each of these approaches provides valuable insight about the range of possible optimal decision paths and evolution of the system in the face of uncertainty, they lack the fundamental characteristic of solving for an adaptable or flexible solution due to the nature of the underlying deterministic model they use. Though alternate scenarios are tested, the model is structured assuming perfect foresight, which does not account for the real-world opportunity to learn and revise decisions throughout the planning horizon.

### *3.3.3 Formal Stochastic Approaches*

For identifying adaptive decisions under uncertainty, formal stochastic optimization or other sequential decision under uncertainty methods are needed. Klein et al. (2008) develop a small research scale stochastic dynamic programming model of the U.S. electricity market to study generation expansion under long-term uncertainties such as fuel price and (future) carbon emissions regulation. Stochastic dynamic programming (SDP) is the stochastic extension of the deterministic dynamic programming global optimization method, retaining features of the underlying decision-tree it seeks to solve and solution through backward induction using the Bellman algorithm. However, while SDP provides a method for identifying adaptive strategies assuming an opportunity to learn about the uncertain quantity, a challenge to its application is the "curse of dimensionality" (Powell, 2007). This characteristic is seen in the case of Klein et al. (2008) where the number of uncertainties were limited and coarsely discretized into three levels—high, medium, and low. SDP programs grow exponentially large with the number of candidate decisions, uncertainties, and decision periods.

Stochastic programming (SP) methods have been extremely popular for incorporating uncertainty analysis into models of energy systems and the environment, and most of the work integrating uncertainty into electricity generation expansion planning models used to inform the policy process has been on this front. Stochastic programming is built upon the concept of recourse, which provides a method for representing flexible decisions that can adapt to new information. Models are often structured as linear programs where uncertainty is incorporated by integrating a scenario tree with each branch from the root node to a leaf node representing a full set of decisions and uncertainties. The problem is then solved as either a deterministic equivalent of the stochastic problem (i.e., one large LP model) or through decomposition methods (Birge & Louveaux, 1997).

A stochastic programming formulation for the GENIE global electricity planning model was developed, where the learning-by-doing rate is uncertain (Mattsson, 2002). Likewise, the MARKAL global energy systems model and the WITCH hybrid model have stochastic programming formulations where uncertainty about carbon reduction targets and uncertainty about the effectiveness of R&D programs, respectively, are explicitly considered (Ybema et al., 1998; Bosetti & Tavoni, 2009). The ERIS electricity model for energy research investments also has a stochastic programming version, which has the ability to consider stochasticity in carbon targets, learning rates, and electricity demand (Kypreos & Barreto, 2000). Finally, Botterud et al. (2005) present a research-scale stochastic programming model for making electricity generation investments in the context of both centralized and decentralized markets, and uncertainty in electricity demanded is considered.

The popularity of using stochastic programming to structure sequential decision under uncertainty models for investment planning in the electricity sector reflects its ability to rigorously and explicitly represent multiple, history dependent processes and solve for optimal adaptive decision paths (Powell, 2012). However, the method does retain its own limitations, as seen through the individual applications above.

First, due to the use of exogenous scenario trees to represent the range of uncertainties, SP can also suffer from the curse of dimensionality, where the size of the problem grows exponentially large with the number of uncertainties and time periods considered. The GENIE, MARKAL, WITCH, and research-scale model of Botterud et al. described above all limit the number of uncertainties they incorporate and the number of discrete levels of each uncertainty being considered. For example, in the GENIE SP formulation, the uncertainties incorporated are discretized into only two different levels for the learning rate (i.e., low and high). Such coarse discretization keep the models tractable. In the case of the ERIS stochastic program, the model is kept tractable by limiting the number of decision stages to two.

Second, due to the scenario tree nature of SP and the requirement to generate the trees in advance, incorporating path-dependent stochastic processes remains a dimensionality challenge for the SP method as well. This feature can limit study of important endogenous uncertainties such as the potential dependence of future likelihood of R&D successes on the amount of R&D invested.

One method not discussed above but is emerging in energy systems investment planning is the use of modern portfolio theory (MPT) to incorporate risk into decision making. First introduced in the early 1950s, MPT is today a widely used technique in finance, which advocates diversifying assets to reduce overall risk in a financial portfolio (Markowitz, 1952). In a recent master's thesis at the University of Illinois at Urbana-Champaign, MPT was applied to electric power generation expansion planning, showing that adding a risky technology (e.g., high fuel costs, low technology development trajectory) to an already relatively high risk generation portfolio reduces the overall risk (lowers total system costs) (Beltran, 2009). While this work shows the potential for applying portfolio theory to investment planning in the electricity sector, the model used treats different types of power plants as perfect substitutes for one another—as with pure financial securities—by assuming fixed operations (i.e., capacity factors) for them. Thus, Beltran is not able to fully capture the effect that complementarity between technologies might have on the optimal investment plan under uncertainty. An engineering cost-based electricity model that solved for the optimal dispatch of power plants within an electricity system would provide additional insight.

Finally, a promising and still emerging method for power systems planning extends the stochastic dynamic programming framework by incorporating techniques for explicitly managing problems with multiple decision stages, multiple uncertainties, and path dependency. Approximate dynamic programming (ADP) is a numerical dynamic programming approach for implementing SDP by efficiently exploring the decision space for complex problems under uncertainty precisely when the dimensionality becomes too large. ADP iteratively samples potential decisions and uncertainties using Monte Carlo techniques, approximates traditional Bellman value functions from those samples using either gradient search or regression-based techniques, and uses the approximations to solve for optimal decisions (Powell, 2007; Bertsekas, 2007; Parpas & Webster, 2012; Godfrey & Powell, 2002). An example of applying approximate dynamic programming in the context of sequential decision making in electricity generation expansion is seen in the SMART model, developed at Princeton University (Powell et al., 2012). SMART is an engineering-cost integrated model for decision making about power plant dispatch, electricity storage, and long-term generation investments; captures multiple uncertainties including variability in wind resources and rainfall, electricity demand, and fuel prices; and makes decisions sequentially at frequent time steps. It is the only known existing ADP-based model for making long-term electricity investment generation decisions, and although relevant limitations exist with respect to the method for value function approximation used and the complexity of the model for developing new applications, it represents the general ADP framework upon which this dissertation builds.

Outside the electricity generation investment planning literature in the broader area of economic energy and environmental policy modeling, there have been a few studies that have explicitly incorporated uncertainty into decision models. However, most of them rely on reducing the dimensionality of the problem in a manner that limits either the analysis or interpretation of the solution achieved (Golub et al., 2011).

First, using stochastic programming methods, Bosetti and Drouet (2005) develop an economy-climate growth model using SP to study optimal R&D investments and climate abatement under uncertainty about the effectiveness of R&D investment. However, they use a coarse discretization of uncertainties to manage the resulting dimensionality. Solak et al. (2010) present a general analytic SP for optimization of R&D investment portfolios under endogenous uncertainties and in a multi-stage context, but also use (only two) discrete realization levels to represent uncertainty. Baker and Solak (2011) develop a stochastic program using the DICE model framework to study the same question under endogenous path-dependent technological change uncertainties. However, their formulation requires a customized deterministic mapping function to assign outcomes to decisions, which limits the generalizability of the framework to other applications.

A few other studies have formally framed environmental (climate) decision problems under uncertainty as a multi-stage stochastic dynamic program, using a variety of approaches to overcome the dimensionality challenge. Gerst et al. (2010) develop a SDP formulation of the DICE model to explore optimal climate policy under potential extreme climate change-related economic damages. However, they use discrete sampling via experimental design and a very large number of iterations to learn about the solution space, which can be computationally very expensive. Kelly and Kolstad (1999) and Leach (2007) base their stochastic climate policy models on the DICE framework as well, and study optimal climate policy under uncertainty in the climate system response to carbon emissions. In their studies, they approximate the value function associated with the Bellman equation using neural networks to estimate a functional form with 16 terms, but ultimately use discrete gridded samples in state-space to iteratively improve the approximation. Finally, Crost and Traeger (2010) and Lemoine and Traeger (2011) also study optimal climate policy under climate change uncertainty using a SDP formulation of the DICE model; they statistically estimate relationships between state variables offline in order to reduce the dimensions of the state vector, and then use conventional backward induction on the reduced state-space. Overall, each of these approaches rely on discretizing a (possibly reduced) state-space into intervals, and therefore require potential compromises of resolution and accuracy. Most recently, Webster, Santen, and Parpas (2012) contributes to the growing DICE stochastic optimization modeling community by presenting an approximate dynamic programming formulation of the DICE model, incorporating endogenous, path-dependent continuous uncertainty in technological change in a multi-stage decision context. Their work shows the value of the ADP framework to study optimal decisions under decision-dependent uncertainties and to explicitly overcome the dimensionality challenge of SDP without loss of accuracy.

This dissertation contributes to this literature by applying an approximate dynamic programming method to R&D and capital investment planning under technological change uncertainties, but in the engineering cost-based long-term electricity generation planning context. In doing so, it seeks to bridge the gaps in modeling practices between the three sets of literature reviewed above—it seeks to develop a decision support model with adequate resolution of the critical structure of the electricity system, explicit detailed learning-by-doing and learning-by-searching technological change dynamics, and an efficient method for exploring adaptive, sequential decisions under uncertainty.

Next, an introduction to the new modeling framework with learning-by-searching technological change under static (deterministic) planning is provided.

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# Chapter 4 Investment Planning under Endogenous Technological Change: Description of the Deterministic Modeling Framework

The purpose of this chapter is to introduce the numerical modeling framework developed and used for the deterministic study on optimal electricity generation technology R&D and capital investment strategies under endogenous learning-by-doing (LBD) and learning-by-searching (LBS) technological change. The first section outlines the overall structure of the problem. The next three sections detail the formulation of the optimization model, focusing on the structures introduced to represent technological change dynamics and electric power system characteristics. The following two sections provide information about the data used to build the reference model, and details about how the model is solved. Finally, the last section presents results from running the reference model and shows the optimal investment strategy under a reference scenario.

## 4.1 Overall Structure of the Problem

This dissertation employs the framework of a traditional least-cost electricity generation capacity expansion optimization model (e.g., Turvey & Andersen, 1977; Hobbs, 1995), and modifies it to simultaneously choose R&D investments for emerging low-carbon technologies (i.e., coal with carbon capture and sequestration, nuclear, wind, and solar). To do this, it builds upon previous modeling work in this area, incorporating both endogenous learning-by-doing and endogenous learning-by-searching dynamics (e.g., Messner, 1997; Barreto & Kypreos, 2004; Fischer & Newell, 2008). The base model is a capital investment planning model at its heart, but with generation technology costs responding to decisions about capital investments as well as technological innovation. To the state of the art, this work adds the capability to study detailed drivers behind learning-by-searching technological change through an explicit two-factor formulation for new knowledge gained about these emerging technologies (e.g., Jones, 1995; Porter & Stern, 2000; Popp, 2004). Figure 4-1 provides a structural overview of the new modeling framework.

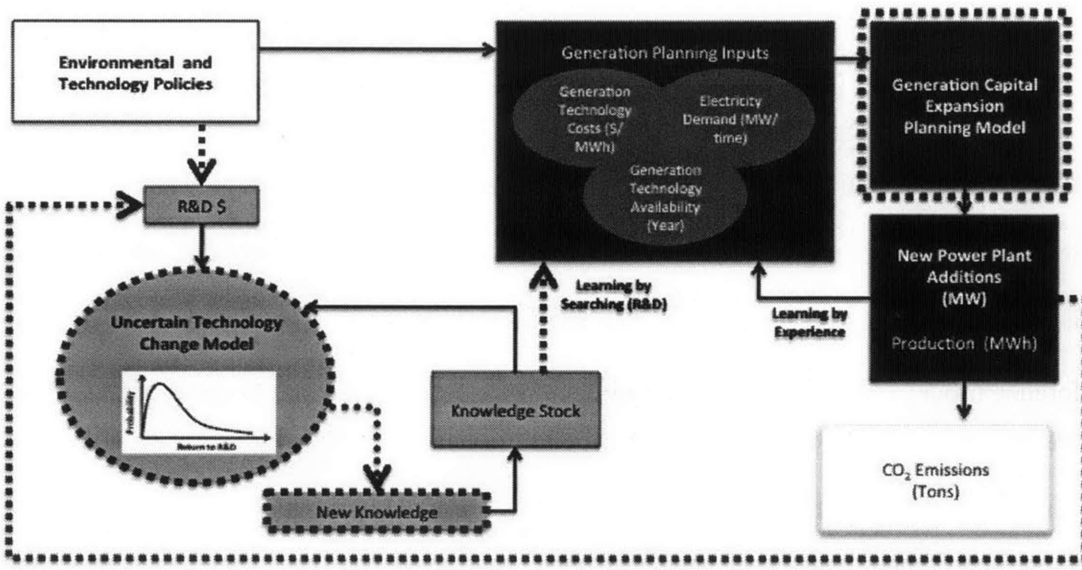


**Figure 4-1. Overview of the new modeling framework for electric power generation R&D and capital investment planning**

The planning horizon is 60 years, with generation capital and R&D investment decisions made every five years. Five-year periods are used to account for the approximate time it takes for innovation activity to maximally affect energy use (Popp, 2001). In this framework, LBS-based technological change proceeds via a lumped entity consisting of all public and private entities (e.g., private equipment manufacturers, government labs) engaged in energy innovation activity applicable to the electric power sector. Further, LBS-based technological change is defined as the broad base of innovative activity with an ability to cause component-wise reductions in the cost of energy technologies; from the perspective of basic versus applied research, LBS-based technological change in this model spans a continuum including both types of research (Clarke et al., 2008, Clarke et al., 2006). The existing physical system is also represented and is based on aggregate United States generating capacity and electricity demand. Finally, given the long-range strategic policy and technology planning objectives of this research, and the large structural uncertainties inherent in the short-term market behaviors of individual firms over such long time scales, a centralized planning approach is used (Pérez-Arriaga & Meseguer, 1997). This formulation designates a hypothetical central decision maker to simultaneously make investment and generation decisions [3]. Doing so also keeps the core evaluation model tractable during the second phase of the dissertation on decision making under uncertainty. The full model formulation and all variable and parameter definitions are presented in Appendix A. The key features of the model and associated data are presented below.

[3] Using a central planning approach also assumes perfect competition in the electricity markets, and no R&D market failures, such as knowledge spillovers.

## 4.2 Objective and Key Constraints

The objective follows a traditional least-cost electricity generation expansion planning problem, with modifications to include choosing investments in R&D and representing the resulting technological change. In each period, the planner chooses $NEW\_CAPACITY_{t,g}$, the new generation capacity for technology $g$ to install in period $t$, and $REBACK_{t,g}$, the allocation of R&D investments into technology category $g$ in period $t$, to minimize the net present value of total system costs:

$$\min_{NEW\_CAPACITY_{t,g}, REBACK_{t,g}} \sum_{g,t}^{G,T} \left[FC_{t,g} + VC_{t,g} + REBACK_{t,g}\right](1+r)^{-t},$$

where $FC_{t,g}$ represents the total fixed costs (overnight capital and fixed O&M costs) of technology category $g$ in period $t$, $VC_{t,g}$ represents the total variable costs (fuel and variable O&M costs) of technology $g$ in period $t$, and $r$ is the discount rate.

In addition to constraints that define the design and operation of the electric power system (summarized below and detailed in Appendix A), one key constraint drives the optimal new generation capacity and R&D investment strategy in this problem:

$$\sum_{t}^{T} E_t \leq ecap, \text{and}$$

where *ecap* represents the total cumulative allowable carbon emissions from the electricity sector during the planning horizon (a cumulative emissions cap). Stated simply, the constraint forces the objective to be met by allocate the quantity of emissions in each period from the total allowable cap. Tying this back to the research questions framed above, allocating emissions between periods defines direct emissions cuts "now versus later" and the effort allocated to currently available technology adoption. R&D expenditures between periods define the indirect emission cuts "now versus later" and effort spent on innovation and new technology development. Together, these decisions and constraint inform the economically-efficient balance of the two pathways for long-term emissions management described above.

## 4.3 Technological Change Dynamics

Technological change enters the model through two distinct, but complementary pathways. Building on recent empirical and numerical modeling literature, this model employs a two-factor learning curve (2FLC) to simultaneously represent learning-by-doing and learning-by-searching (Klaassen et al., 2005; Soderholm & Klaassen, 2007; Miketa & Schrattenholzer, 2004; Barreto & Kypreos, 2004). Through the 2FLC, the cost of a technology falls as the stock of knowledge about that technology increases, and the physical experience with that technology increases. In the current framework, both types of technological change affect the overnight capital cost component of total fixed costs of the emerging technologies: wind, solar, coal with carbon capture and sequestration (CCS), and nuclear. The current model specifies experience with a technology by its cumulative installed capacity (total GW).

The technological change dynamics represented in the model can be summarized with the three key equations:

$$NEWHEB_{t,g} = \alpha_g REBACK_{t,g}^{\beta} HEBACK_{t,g}^{\phi} \qquad \text{(Eq. 4.3.1)}$$

$$CAPC_{t,g} = \frac{CAPC_{0,g}}{(CAPACITY_{t,g}^{\eta 1_g})(HEBACK_{t,g}^{\eta 2_g})} \qquad \text{(Eq. 4.3.2)}$$

$$HEBACK_{t+1,g} = NEWHEB_{t,g} + \delta_g HEBACK_{t,g} \qquad \text{(Eq. 4.3.3)}$$

The first equation, 4.3.1, represents the production of new knowledge for technology $g$ in time period $t$, $NEWHEB_{t,g}$, defining it as a function of R&D investment, $REBACK_{t,g}$, and the human knowledge stock, $HEBACK_{t,g}$, for technology $g$ in time period $t$, with diminishing returns to research (both $\beta$ and $\phi$ are less than 1.0) through an "innovation possibilities frontier" (IPF). The parameter $\beta$ represents the contribution of R&D dollars invested to the creation of new knowledge, $\phi$ represents the contribution of the current knowledge stock to the creation of new knowledge, and $\alpha$ is a technology-specific scalar used to calibrate the behavior of the new innovation possibilities frontier to the current learning-by-searching literature.

The second Equation, 4.3.2, represents the two-factor learning curve combining LBD and LBS. $CAPC_{t,g}$ is the capital cost of technology $g$ in time period $t$, $CAPC_{0,g}$ is the initial capital cost, $CAPACITY_{t,g}$ is the total installed capacity in GW of technology $g$ in time period $t$, $HEBACK_{t,g}$ is again the human knowledge stock for technology $g$ in time period $t$, and $\eta 1_g$ and $\eta 2_g$ are the learning-by-doing and learning-by-research output elasticities for technology $g$, respectively. As noted by the index, the parameters $\eta 1_g$ and $\eta 2_g$ are technology specific; their interpretation follows directly from traditional experience curve "progress-ratio" calculations where $1 - 2^{\eta i}$ describes the cost reduction that occurs from a doubling of capital stock ($\eta 1$) *or* knowledge stock ($\eta 2$) (Ibenholt, 2002).

Equation 4.3.3 represents the cumulative nature of LBS-based knowledge accumulation, and shows the stock nature of the human knowledge dimension in this problem, where $NEWHEB_{t,g,}$ is new knowledge gained through R&D effort in technology $g$ during period $t$, and $\delta_g$ represents a technology-specific decay rate for human knowledge from one period to the next.

Use of the innovation possibilities frontier is where the formulation of the endogenous LBS technological change in this energy systems planning model diverges from the current modeling literature. Typically, endogenous LBS representations define new knowledge as equivalent to the dollars of R&D invested, and knowledge stocks as a simple accumulation of R&D invested over time (e.g., Barreto & Kypreos, 2004; Miketa & Schrattenholzer, 2004). Motivated by the current empirical literature that shows the production of new knowledge is dependent upon the quantity and quality of current knowledge, in addition to the direct R&D investments, modeling LBS technological change through an innovation possibilities frontier allows one to study the contributions of these effects separately. Also, recent empirical study suggests that the knowledge stocks of different technologies categories can behave quite differently with respect to diminishing returns (Popp, Santen, Fisher-Vanden, & Webster, 2012); the current formulation provides a platform to analyze the effects of these variations across technologies on optimal investment strategies. Finally, disaggregating the R&D investment effect from the knowledge stock effect facilitates a more direct representation of uncertainty in the returns to R&D investment, while continuing to utilize information retained in accumulating knowledge stocks, as explored in Chapters 6 and 7.

## 4.4 Electricity System Operations

The infrastructure and operations of the electric power system, and behavior of electricity consumers, interact in ways that make it difficult to assess a priori the effect of cost reductions in specific emerging technology categories on optimal new capacity additions and actual emissions reduction. Electricity demand must be (effectively) met in real time by electricity generated, as there is for all practical purposes no efficient storage on the system. This demand varies throughout the day, week, and year. Certain thermal generating units such as coal or nuclear power plants can become less efficient at generating electricity at low load levels, are expensive to "turn up" and "turn down" throughout the day to meet this demand, and have relatively inexpensive fuel prices, making them a premier default choice for "baseloading," or running near their full capacities most of the time. Renewable resource generating technologies, such as wind and solar power, are characterized by intermittency, fueled by geophysical laws that dictate where and when the wind blows and the sun shines. Such characteristics create a dynamic interaction between the operation and "dispatch" of different generating technologies during different times of the day and under different environmental and cost conditions—with certain technologies "filling in" for other technologies in different orders. Finally, a criterion that electricity supply ought to be reliable and that consumers should be able to depend on power without serious interruption issues directs power system planners to build in redundancy, such as in the form of capacity reserve margins over peak electricity demand and operating reserves.

A modified, least-cost electricity generation capacity planning optimization model is used for this study in order to explicitly capture these effects and many of the constraints that make the problem so unique. As Appendix C shows, the dynamics at play within the power system affect the strategies for emission reduction, and these interactions are often missed in the economic models used for climate policy analysis that assume fixed operations to study electricity-related emissions. In order to isolate and study the effects of technological change, the model in this dissertation employs a streamlined version of what can become a more comprehensive treatment of the physical system during future exploration. Still, several of the effects described above, outlined through the following four main equations and elaborated on in Appendix A are represented.

$$\sum_{g^*}^{G^*} PWROUT_{t,d,g^*} = NETLOAD_{t,d} \qquad \text{(Eq. 4.4.1)}$$

$$NETLOAD_{t,d} = demand_d(1+k)^t - PWROUT_{t,d,g^{**}} \qquad \text{(Eq. 4.4.2)}$$

$$PWROUT_{t,d,g^{**}} = CAPACITY_{t,g^{**}} availability\_rate_{g^{**}} \qquad \text{(Eq. 4.4.3)}$$

$$\sum_{g}^{G} CAPACITY_{t,g} \geq demand\_peak(1+k)^t(1+reserve\_margin) \qquad \text{(Eq. 4.4.4)}$$

Electricity demand is specified using an annual load duration curve defining the number of (non-consecutive) hours that electricity demand is at or below a certain power level, dividing the year into sixteen time slices, and including a "super peak" that represents the forty hours with the highest electricity demand over the year. A nationally aggregated version of the U.S. load from 2006, as used by the National Renewable Energy Laboratory (NREL) ReEDS base model and shown in Table 4-1 and Figure 4-2 below is used. Every year, the power level for each demand slice grows exogenously by, *k*, shown in Equation 4.4.4.

**Table 4-1 Annual U.S. Electricity Loads by Demand Slide** (Short et al., 2009)

| **Demand Slice** | **Season** | **Time Period** | **Duration** (Hours) | **Power** (GW) |
|---|---|---|---|---|
| H1 | Summer | 10PM – 6AM | 736 | 453 |
| H2 | Summer | 6AM – 1PM | 644 | 482 |
| H3 | Summer | 1PM – 5PM | 328 | 606 |
| H4 | Summer | 5PM – 10PM | 460 | 602 |
| H5 | Fall | 10PM – 6AM | 488 | 375 |
| H6 | Fall | 6AM – 1PM | 427 | 420 |
| H7 | Fall | 1PM – 5PM | 244 | 478 |
| H8 | Fall | 5PM – 10PM | 305 | 485 |
| H9 | Winter | 10PM – 6AM | 960 | 390 |
| H10 | Winter | 6AM – 1PM | 840 | 445 |
| H11 | Winter | 1PM – 5PM | 480 | 440 |
| H12 | Winter | 5PM – 10PM | 600 | 474 |
| H13 | Spring | 10PM – 6AM | 736 | 369 |
| H14 | Spring | 6AM – 1PM and 1PM – 5PM | 1104 | 433 |
| H15 | Spring | 5PM – 10PM | 368 | 453 |
| H16 | Summer | Superpeak | 40 | 722 |

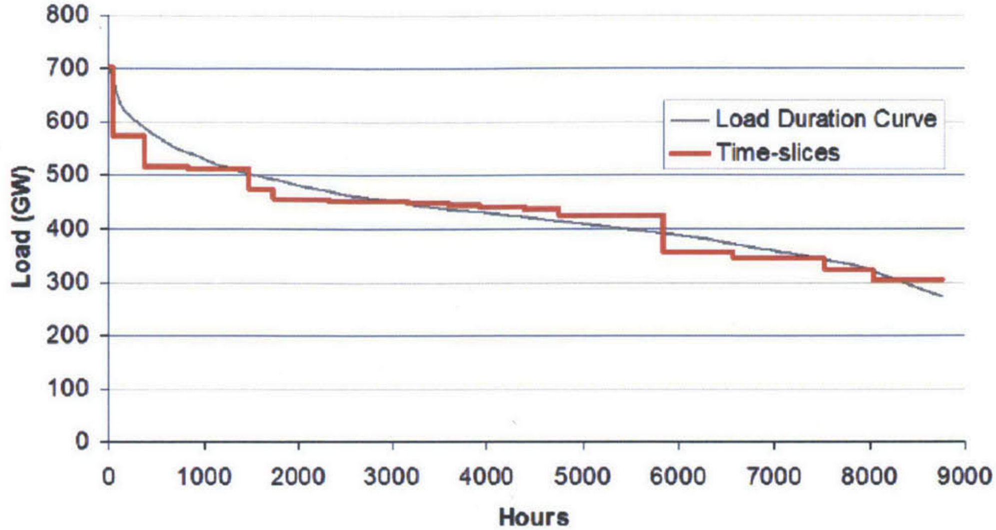

**Figure 4-2 Annual U.S. National Load Duration Curve in ReEDS Model** (Short et al., 2009)

Equation 4.4.1 describes a fundamental characteristic about the nature of current power systems that do not effectively store electricity—that power generated must equal power consumed. To accommodate intermittency in renewable generation, this defining characteristic is represented using a net load approach. In this approach, the power output, $PWROUT_{t,g*}$, of *dispatchable* technology, $g*$, in time period, $t$, and demand slice, $d$, must equal the total electricity demanded in time period $t$ and demand slice $d$ less the amount electricity supplied by *non-dispatchable* technologies, or the $NETLOAD_{t,d}$. Equations 4.4.1 and 4.4.2 explicitly outline this approach. Non-dispatchable technologies, $g**$, are defined as nuclear power plants (due to their operational constraints and generally baseloaded nature) and solar plants, which are represented as running whenever available (subject to maintenance schedules and expected outages). Equation 4.4.3 outlines this approach, showing that an exogenous technology specific *availability_rate* is used. All other technologies are defined as dispatchable, including wind power, which is represented in this way to model the assumption that wind power can be curtailed. Additionally, solar technology is represented as operating only during the demand slices that correspond to the daytime. The combination of these representations allows modeling to first-order the effects of intermittent renewable resources, as well as the dominant operational constraint of nuclear power plants. Equation 4.4.4 implements a reliability requirement through a constraint that says the sum of all generating technology capacities, *g*, in each time period must meet or exceed the total peak electricity demand in each time period, plus an exogenous *reserve_margin* defined in percentage terms.

Finally, several additional realities are incorporated into the model to represent various aspects of the electric power system. In actuality, each of these can be treated and modeled with more rigor; simplified versions of these realities are included for this study. First a high retirement rate for old coal and old steam gas technologies is assumed. There is a very large capacity of very old conventional coal and steam gas plants in the United States that is expected to be retired in the next one to two decades. A retirement rate for nuclear power is also included, which follows a slightly higher than expected retirement rate based on its expected lifetime given the aging stock of nuclear power plants in the U.S.

Second is a "no new build" constraint on old coal plants, old steam gas plants, and conventional hydro (run of the river) power plants, since these technology types are either likely to still be operational within the problem planning horizon (e.g., hydro), or will be replaced by more efficient technologies (new/advanced coal and new gas). Hydropower in the United Sates is also at or very near its resource constraint, adding to the limitation on new builds in the upcoming years.

Third, to represent existing constraints in the "electricity generation and innovation systems nexus" related to the ability to scale up emerging technologies, such as limited technology availability from suppliers or permitting constraints, a constraint on the rate of change of installed capacities for emerging technologies has been included. This constraint requires that for coal with CCS, nuclear, wind, and solar, the total installed capacity in time $t+1$ for each cannot exceed twice the capacity in time $t$.

## 4.5 Data

The new modeling framework is demonstrated by studying optimal capital and technology R&D investments for an approximation of the U.S. electric power generation sector. The base-year electricity system upon which new capacities are built roughly matches the existing U.S. electric power system in terms of technology types and gigawatts installed, as documented by the U.S. Energy Information Administration (EIA) (EIA, 2009b). As noted above, electricity load data is also based on an aggregate U.S. demand, as used by the National Renewable Energy Laboratory's (NREL) Regional Energy Deployment System (ReEDS) Model (National Renewable Energy Laboratory, 2009). Electricity generator data such as heat rates, fixed O&M costs, initial capital costs, and emission rates are also acquired from NREL and EIA, and shown in Table 4-2 below. Base fuel prices for coal and natural gas are $2.07 and $9.10 per MMBtu, respectively (EIA, 2011b). Uranium prices are given by the Royal Academy of Engineering (2004) at $6.20 per MMBtu.

Technology learning data, shown in **Table 4-3**, is given by Barreto and Kypreos (2004) and Popp (2006)[4]. Specific values for the scalar a in the innovation possibilities frontiers for emerging technologies are derived by calibrating new knowledge creation via an innovation possibilities frontier (IPF), and resulting capital cost reductions to cost reductions from the original two-factor learning-by-searching indices in the literature (See Appendix B). This calibration method retains the overall impact of knowledge stock on capital cost reduction, but still allows for disaggregation of the dynamics by which new knowledge is created (and thus the knowledge stock accumulates). Knowledge stocks for all technologies begin at 1.0. All additional parameter definitions and values are listed further in Appendix A.

It is noteworthy that for the purposes of developing the stylized model for this dissertation, *a* set of assumptions about the dynamics of the power system and the energy innovation system were necessary to adopt. Furthermore, it was necessary to settle upon *a* set of published cost and technical data for power plant investments and operation to construct the new model, even though several additional (and numerically different) sets of cost and engineering data exist. It is beyond the scope and purpose of this dissertation to apply and analyze results under several different sets of data, but it is important for the reader to recognize that the results of the reference model shown in Section 4.7 and the analyses in Chapter 5 are sensitive to the assumptions made. Therefore, while in the presentation of results and the discussion, references will be made about model behavior using technology-specific names such as "coal with CCS," "wind," or "solar," these

[4] LBD and LBS rates differ significantly across studies, as there are several open research questions that exist in how rates are defined and estimated (Soderholm & Sundqvist, 2007). For the purposes of constructing the new modeling framework for the dissertation exercises, one set of learning rates was applied. Future work may focus on sensitivity analyses and application of additional data sets from the literature.

statements are necessarily tied to the original assumptions and data sets used for this specific numerical implementation. Caution should be exercised before generalizing the results to *specific* technology groups for real-world industry or policy applications.

## 4.6 Solution Approach

Conventional least-cost electricity generation investment planning problems without endogenous learning dynamics are typically formulated as linear or mixed-integer programing problems—linear if the capacity decisions are chosen from a continuous range of megawatts to install, and mixed-integer if power plants are treated as entities with a specific capacity (size) and the decision involves the number of discrete plants of each technology to install. Introducing endogenous learning dynamics changes the structure of the problem into a non-linear programming problem. The non-linearities introduced arise from two separate points within the formulation: the two-factor learning curve shown in Equation 4.3.2 and the innovation possibilities frontier shown in Equation 4.3.1 above in Section 4.3. (Note that even a single-factor endogenous learning curve with either learning-by-doing or learning-by-searching would create a non-linearity.) As such, the problem is solved numerically within the GAMS modeling environment, using a standard non-linear programming solver, CONOPT. A 10-point seeding algorithm is also used to set a scattered grid of initial points and start the optimization from different locations within the solution space. The optimum preserved is that which minimizes total system costs across the ten seeds.

Terminal conditions for this multi-period decision problem are managed by running the 60-year planning problem for an additional 40 years (after which electricity demand growth stops and all operations cease). Results from only the first 12 (5-year) periods are used in each of the analyses, ensuring that decisions being made at or near the end of the planning horizon are not "end-of-world" artifacts or a result of arbitrary terminal condition assumptions.

**Table 4-2 Electricity Generator Data** (Short et al., 2009; EIA, 2011b; Royal Academy of Engineering, 2004)

| Technology | Initial Capacity [GW] | 5-year Retirement Rate [%] | Heat Rate [MMbtu/MWh] | Initial Capital Cost [$/kW-knowledgeunit] | Fixed O&M Cost [$/kW-year] | Initial Fuel Cost [$/MMBtu] | Other Variable Cost [$/MWh] | Emissions Rate [lbs/MMbtu] | Annual Availability Rate [%] |
|---|---|---|---|---|---|---|---|---|---|
| Old Coal | 314.294 | 15 | 10.00 | 1234 | 24.460 | 2.07 | 4.14 | 204.12 | 85 |
| New Coal | 1.00 | - | 8.80 | 3167 | 35.970 | 2.07 | 4.25 | 204.12 | 85 |
| Coal with CCS | 1.00 | - | 12.00 | 5099 | 76.620 | 2.07 | 9.05 | 20.41 | 85 |
| Old Steam Gas | 84.267 | 20 | 9.46 | 390 | 25.256 | 9.10 | 3.85 | 121.83 | 80 |
| Gas Combustion Turbine | 196.623 | - | 6.43 | 1003 | 14.620 | 9.10 | 3.11 | 121.83 | 85 |
| Gas Combined Cycle | 120.382 | - | 9.75 | 665 | 6.700 | 9.10 | 9.87 | 121.83 | 90 |
| Hydro | 78.518 | - | 10.34 | 1320 | 12.700 | - | 3.20 | - | 60 |
| Nuclear | 101.004 | 10 | 10.40 | 3016 | 85.663 | 6.20 | 0.48 | - | 90 |
| Wind | 34.296 | - | - | 2438 | 28.070 | - | 5.19 | - | 30 |
| Solar | 1.00 | - | - | 4755 | 16.700 | - | - | - | 95** |

Notes: ** The availability rate for solar is high due to the technology only operating during peak solar demand slices.

**Table 4-3 Reference Scenario Technology Learning Parameters** (Barreto & Kypreos, 2004; Popp, 2006; Appendix B)

| Technology | Learning-by-Doing Elasticity $\eta 1$ | Learning-by-Searching Elasticity $\eta 2$ | IPF a | IPF $\beta$ | IPF $\phi$ |
|---|---|---|---|---|---|
| Coal with CCS [5] | 0.05889 | 0.02915 | 0.3910 | 0.1 | 0.54 |
| Nuclear | 0.05889 | 0.02915 | 0.3910 | 0.1 | 0.54 |
| Wind | 0.25154 | 0.10470 | 0.4389 | 0.1 | 0.54 |
| Solar | 0.41504 | 0.15200 | 0.4536 | 0.1 | 0.54 |

[5] The lack of experience with carbon capture and sequestration technology in the electric power sector makes it difficult to find reliable learning data for use in numerical models of technological change. Thus, other authors have used learning rates for coal $SO_2$ scrubbing technology or $NO_x$ reduction technologies and applied them to coal with CCS technology in numerical decision support models (Rubin, Taylor, Yeh, & Hounshell, 2004). This dissertation uses the history of nuclear fission technology and its learning rates as a proxy for coal with CCS (both are capital-intensive, large baseload technologies with significant challenges of space, scale up, public acceptance, permitting, waste, etc.).

## 4.7 Reference Optimal Investment Strategy

A business-as-usual (BAU) scenario is used to study the reference optimal capital and R&D investment strategy, and the overall effect of introducing learning-by-doing and learning-by-searching into the electricity generation expansion model. Business-as-usual is represented by incorporating a non-binding cumulative emissions cap (*ecap)* equivalent to approximately one-hundred times the 2010 U.S. electricity generation sector carbon emissions (i.e., 300,000 million metric tons), which accounts for proceeding with current operations from years 2010 through 2110 and meeting new electricity demand during this time. As explained in Section 4.6 above, the results from the first sixty years of the model are used for the study; they are compared (Figure 4-3) to results from running the model with all forms of learning on the emerging technologies "turned off" (Figure 4-4).

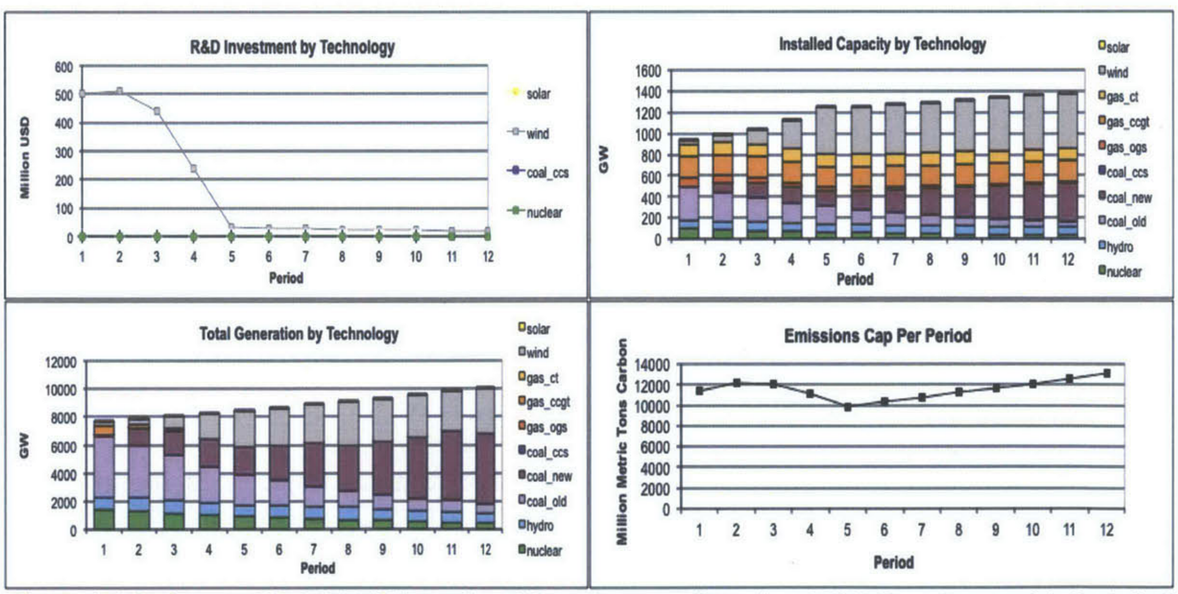


**Figure 4-3 Reference Model (BAU) results with endogenous learning: R&D Investments (a), Installed Capacity (b), Total Generation (c), Emissions Cap by Period (d)**

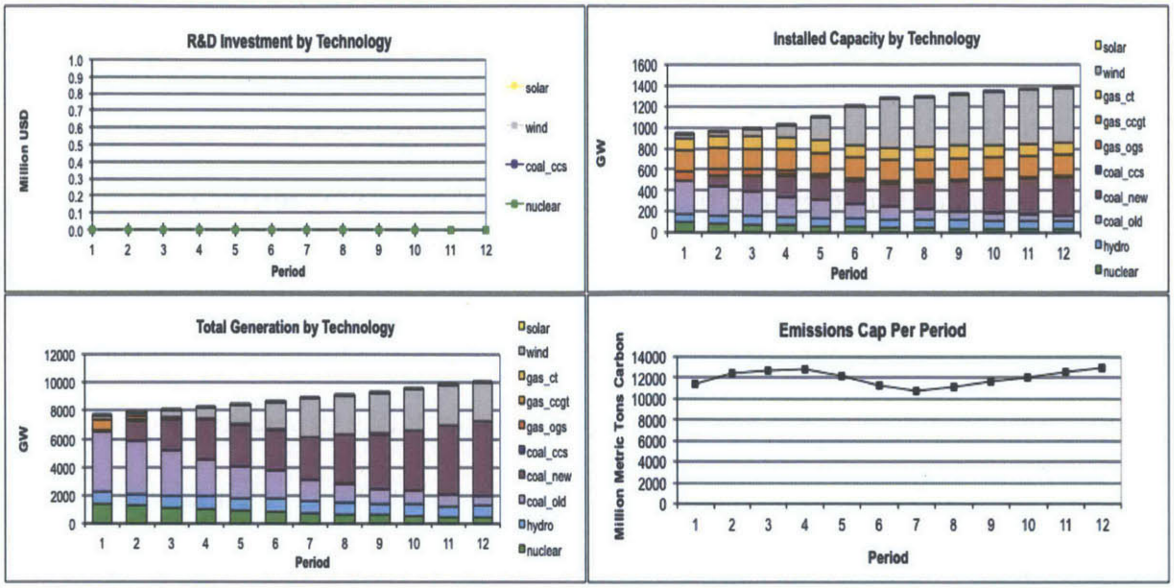

**Figure 4-4 No-learning model BAU results: R&D Investments (a), Installed Capacity (b), Total Generation (c), Emissions Cap by Period (d)**

The optimal solution in the reference model with learning includes investment in wind R&D only, initially relatively aggressively (approximately $500 million) but with dramatic reductions by Period 5 (approximately $30 million) on (Figure 4-3a). Initial capital costs of the other emerging technologies, their specific potentials to learn from R&D, and their overall value in meeting electricity demand and (lack of) emissions constraint, make them sub-optimal to invest in. Still, the optimal investment strategy results in a lower total system cost than when learning is turned off and the option to invest in R&D is not included ($6.048 versus $6.461 trillion NPV, respectively).

Results from both versions of the model show similar trajectories for installed capacities of existing old coal and nuclear plants: existing aging coal plants decline rapidly with time and the constraint on new builds of conventional coal plant technology prevents them from reappearing. Nuclear plants decline less rapidly, following their own retirement rate, but for economic reasons new nuclear capacity is not added. The same is true for the trajectories for all gas-fired power plant types. A comparison of these BAU reference results with results from the well-known industrial-scale NREL ReEDS electricity model show similar behaviors for old coal, new coal, coal with CCS, old steam gas, nuclear, and hydro installed capacities over time. Differences in trajectories and relative magnitudes for wind and natural gas fired plants exist, but are expected given that the ReEDS model contains several additional technologies; detailed, disaggregated natural resource data for renewable technologies such as wind; and the capability to represent transmission constraints within the electricity system (Short et al., 2009). Such capabilities interact to reduce new capacity additions for wind and increase natural gas-fired plants compared to the aggregated U.S. model used in the dissertation. Overall, however, the concordance between the two models' technology capacity trajectories helps validate the new model.

The key difference between the learning and no-learning versions of the new model is in the impact on wind and new coal power (Figure 4-5). Early wind R&D in the presence of learning drops the capital costs of wind technology to a level where it becomes economic to build beginning in Period 1 (and operate in Period 2) instead of new coal plants. However, it is still optimal to build a portion of the new coal plants built in the no learning model, and their longevity allows them to still exist and operate at the end of the planning horizon. Combined with the constraint on the rate of change for installed capacities included in the model for emerging technologies, new low-cost wind power only partially displaces new coal in the reference BAU scenario. Additionally, as Figure 4-5 below shows, the impact is on the timing of capital investment, not the final capacity installations, which by Period 12 are the same. Figure 4-6 shows the capital cost trajectories of all emerging technologies and the corresponding knowledge stocks for the two different models.

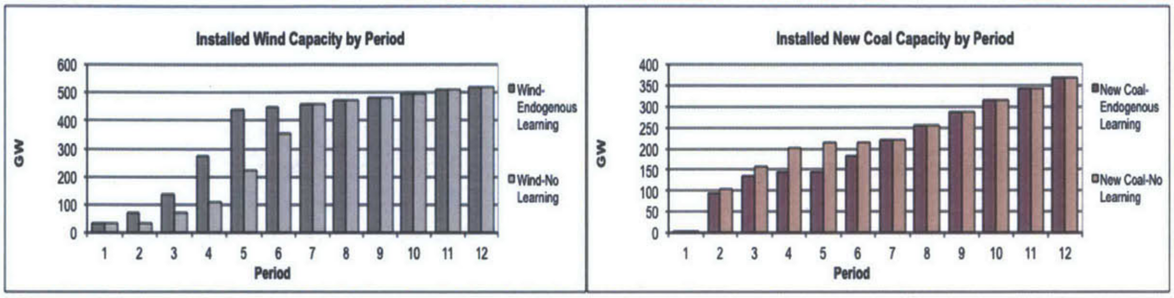


**Figure 4-5 Installed wind (a) and new coal (b) capacities by period in the reference model versus a no-learning model under BAU**

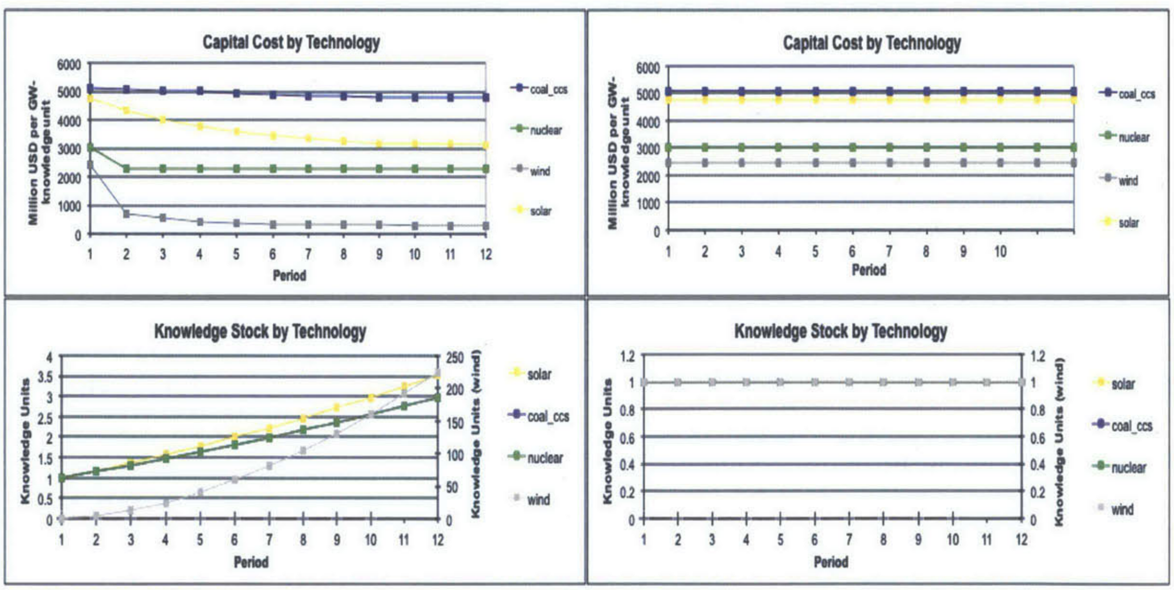


**Figure 4-6 Emerging technology cost and knowledge stock trajectories with endogenous learning in reference model (left) and no learning model (right) under BAU [6] [7]**

[6] Capital costs decrease and knowledge stocks grow at a base (minimum) rate for all learning technologies, regardless of whether they receive real R&D investments. This is an artifact of the model, which adds a minimum level of R&D investment for all learning technologies in the numerical implementation. Note the low rate of knowledge stock increase for solar power in all cases, despite zero R&D investments in the optimal investment strategy.

[7] Note that coal_ccs and nuclear share the same knowledge stock path in the reference model.

Finally, note the delay in suppressed carbon emissions from Period 5 to Period 7 that results from the presence of endogenous learning and R&D (Figure 4-3d and Figure 4-4d, respectively). The reduction in emissions in both sets of results generally corresponds to aggressive retirements for old coal and old gas plants and their corresponding no new build constraints, which are quickly no longer able to operate and force the physical system to settle to a new benchmark before pursuing its true unconstrained emissions path for the remainder of the problem horizon. However, as explained directly above, in the reference learning model, coal generates less because less gets built at this point. The combination of this, along with new capacity and generation, leads to the new benchmark earlier.

In the current formulation of the model, it is shown that it is actually more cost-effective to invest in wind R&D upfront so that you can build more of it and run more of it in later years, than the alternative of building and running new (already inexpensive) coal or natural gas plants, even when there is no emissions reduction objective. While a model with additional real-world power system constraints such as the ReEDS model may reach a different conclusion (e.g., wind would not displace as much fossil-fired plants), this result is presented as a benchmark to study the general behaviors of decision variables in the numerical experiments and sensitivity analyses in the following chapter.

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# Chapter 5 Investment Planning under Endogenous Technological Change: Results from Numerical Experiments and Sensitivity Analyses

This chapter presents results from several numerical experiments and sensitivity analyses to study the behaviors of key variables in the system under different conditions, and to illustrate the capabilities and limitations of the new modeling framework for strategic capital and R&D investment planning. It also presents results from select experiments to demonstrate the value in disaggregating new knowledge creation dynamics for different technologies and for optimizing an investment portfolio under uncertainty. Table 5-1 at the end of the chapter summarizes the assumptions and associated parameters that differ across each of the analyses. The final section, 5.7, provides a summary of and key insights gained from performing each of the numerical experiments [8].

## 5.1 Optimal Investment Strategy v. Carbon Target Stringency

This first experiment demonstrates the new model's capability to jointly optimize R&D and generation capital investment portfolios inter-temporally over different climate objectives. It does so by studying the behavior of the model's main decision variables, per period electricity generation capital investment and per period emerging technology R&D investment. Results from four climate policy stringency levels are compared: 1)

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[8] As described in Chapter 4, the reader should exercise caution before generalizing results from the following analyses to specific technology groups for actual industry or policy applications. Though specific technology names are used below, due to the stylized nature of the model and specific set of cost and technological change data used, insights revealed are intended to provide intuition about optimal investment strategies for broad classes of technologies and general model behavior.

business as usual (BAU), defined as the reference model scenario from Chapter 4.7 above, 2) a "weak" target, defined as reducing the cumulative carbon cap (*ecap)* 25% from BAU, 3) a "moderate" target, defined as reducing *ecap* 50% from BAU, and 4) a "difficult" target, defined both by reducing *ecap* 75% from BAU *and* meeting a final period emissions cap equivalent to approximately 80% below year 2010 BAU emissions. All other parameters and constraints are implemented as they are in the reference model. The full learning version of the model (with both LBD and LBS) is used for this and all following experiments, unless otherwise noted.

Focusing first on investment patterns in Figure 5-1, the set of R&D investments and installed capacities under a weak emissions target can be compared with the BAU (no cap) results. For ease of explanation, the BAU reference model results from Chapter 4.7 are replicated here. Note that while wind R&D investment neither changes in magnitude nor shifts temporally from BAU, coal with CCS R&D gradually enters from Period 1 on. For both technologies, it can be seen that it is optimal to invest in R&D first, and then build new capacity once their capital costs fall. Under this cap however, it is optimal to invest early in wind and begin building it as soon as its capital costs are even slightly reduced (in Period 2). Alternatively, it is optimal to invest in coal with CCS R&D technology more slowly and relatively moderately, waiting for it to get as cheap as possible, and then building it later or just in time to meet the final target when there is no other choice. This is seen by the fact that at the end of the 60-year planning horizon, new coal with CCS capacity only just begins to appear. Compared to the BAU scenario, new coal with CCS capacity displaces a small portion of new (conventional) coal capacity in order to meet the carbon target.

To meet a more moderate emissions reduction target of 50% below BAU (Figure 5-1), wind R&D investment and new capacity patterns continue unchanged from their BAU magnitudes and trajectory. However, coal with CCS technology R&D investment increases and peaks within the 60-year planning horizon under the moderate target, allowing it to become cost competitive with other low-emission technologies earlier and thus also being built earlier, by Period 6. Figure 5-2 presents the trajectories of capital cost and corresponding knowledge stocks for each of the emerging technologies in each scenario. A maximum rate of change constraint for installed wind power capacity, combined with its low resource availability rate, also has a role in promoting new coal with CCS capacity to enter the system. As explained in Chapter 4, the installed capacity for each of the emerging technologies in any one period must not exceed twice its own installed capacity in the preceding period. Thus, over the long planning horizon defined in this problem, there is incentive to invest in a second low-emission technology to meet the final cumulative cap.

Finally, to reach a strong cumulative emissions target plus a stringent final period (Year 60) emissions cap, dramatic changes are seen in the optimal R&D investment trajectory and in the capacity mix (Figure 5-1). In this scenario, nuclear power R&D investment enters and is strong and swift, and coal with CCS R&D increases in the early periods and peaks earlier as well. Throughout this time, wind R&D continues unchanged. The changes that are witnessed occur because coal with CCS (with its only 90% carbon capture rate), and wind (with its lower resource availability rate) do not provide enough opportunity to reach the stringent target. For this, a zero-emission technology, "guaranteed" to provide vast emission reduction due to its baseloaded nature is needed (and therefore targeted). Simply put, the other technologies cannot do enough for such strict targets, so the optimal near-term policy favors the most capable technology. Under the strong target scenario, nuclear power displaces almost all new coal capacity from the BAU, weak, and moderate target scenarios, with some additional new coal with CCS capacity making up the balance.

A relevant question here is why under the strong target scenario does nuclear power R&D investment and new capacity not dominate either coal with CCS or wind power, or both? Why does R&D investment (and corresponding new capacity) occur early, but then drop to a negligible amount only to leave room for the more expensive capital cost technology (Figure 5-1)? The answer relies on the complex cost structure of the generating technologies themselves. The decision to add new capacity depends both on the capital cost of the technologies, as well as other fixed costs and variable costs. In the case of nuclear power, while the capital cost is lower than coal with CCS to begin with, its fuel cost (a dominant portion of its variable cost) is higher. In the case of this problem and specific modeling framework, nuclear technology's capital costs decrease from the R&D investment, but its variable costs remain unchanged. On the other hand, investing in coal with CCS for example, allows the capital cost to decrease, and after a certain point the balance of its fixed and variable costs exceed nuclear power in terms of cost competitiveness. Therefore, the overall R&D focus is still on the coal with CCS and wind even under the strong target, but nuclear R&D investment and new capacity fills in during the early periods before coal with CCS is cost competitive enough. Nuclear power's zero-emission characteristic also helps secure a spot for its investment under this strong target scenario.

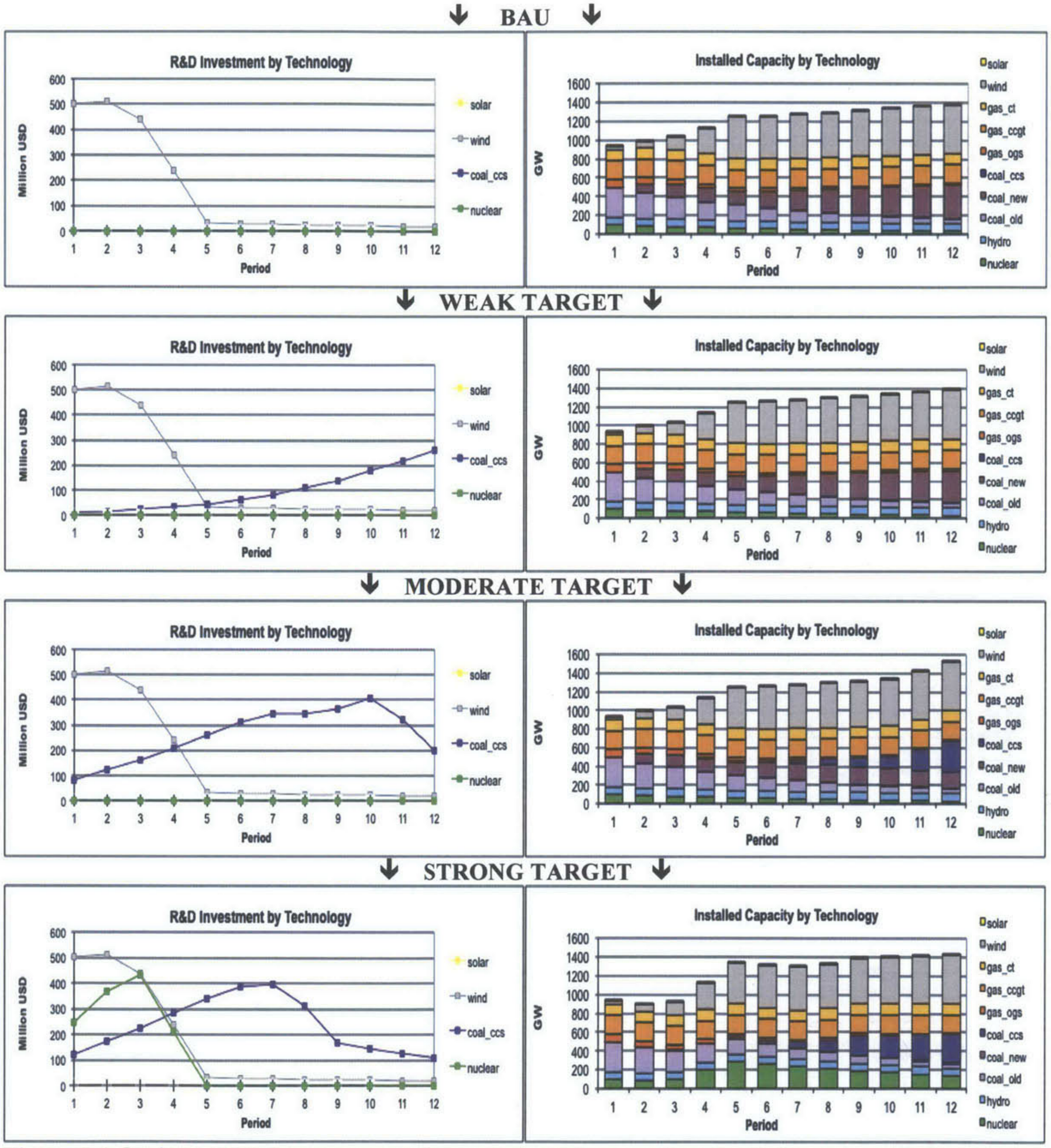


**Figure 5-1 Optimal R&D investments (left) and installed capacities (right) for various carbon reduction target stringencies**

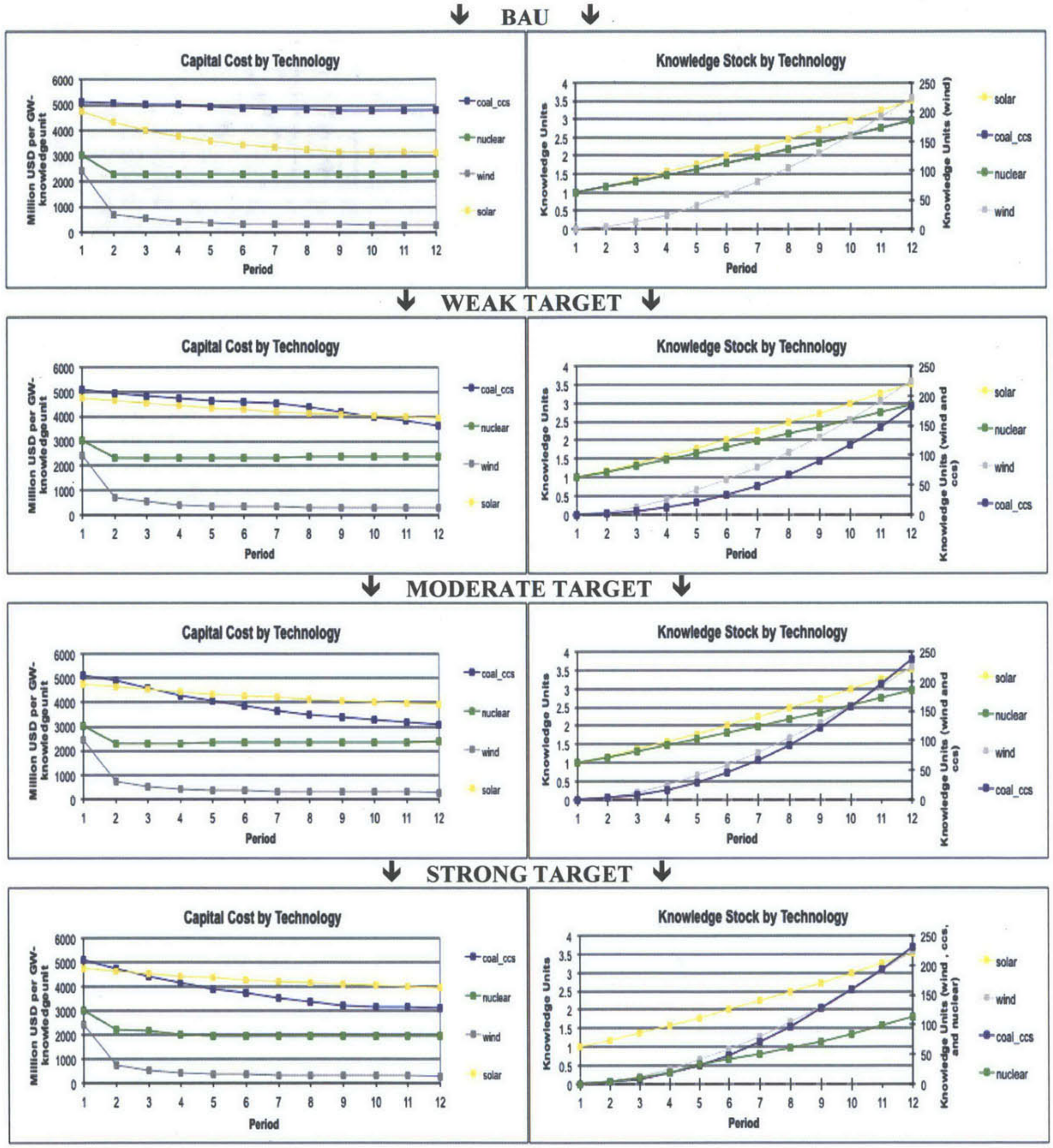


**Figure 5-2 Capital cost (left) and corresponding knowledge stock (right) trajectories for various carbon reduction target stringencies**

Comparing the optimal emissions trajectories in Figure 5-3 below supports the results outlined above. In the first two scenarios of a weak 25% and moderate 50% reduction from BAU, the general strategy is to inch the system *towards* meeting the cumulative goals, but to wait until later—until there is no other choice—to begin building (and operating) still expensive low-carbon technologies (i.e., coal with CCS). In these scenarios, optimal generation patterns for the technologies follow optimal installations fairly closely (See Figure 5-4 and Figure 5-1 for a comparison of generation and installed capacity per period under all carbon targets). This changes under the strong target, where the challenging overall and final strict caps are present, leaving the optimal emissions path a result of investing both in R&D and building and operating new nuclear plants early. Under this strong target, operations no longer mimic installation patterns, and nuclear power generation comprises up to half of the total generation in order to meet this strict final target. This occurs because the system needs nuclear power installed in order to meet the stringent cap, but once nuclear power is installed, it must be run (e.g. it is baseloaded).

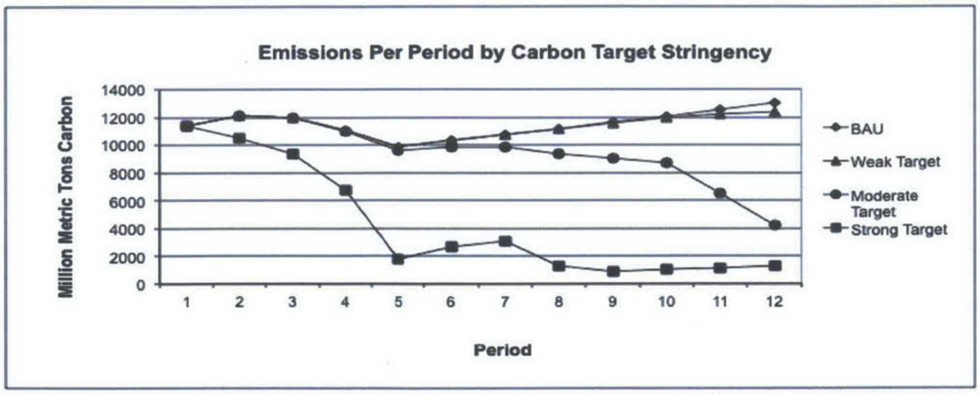


Figure 5-3 Optimal emission profiles (caps) for various carbon reduction target stringencies[9]

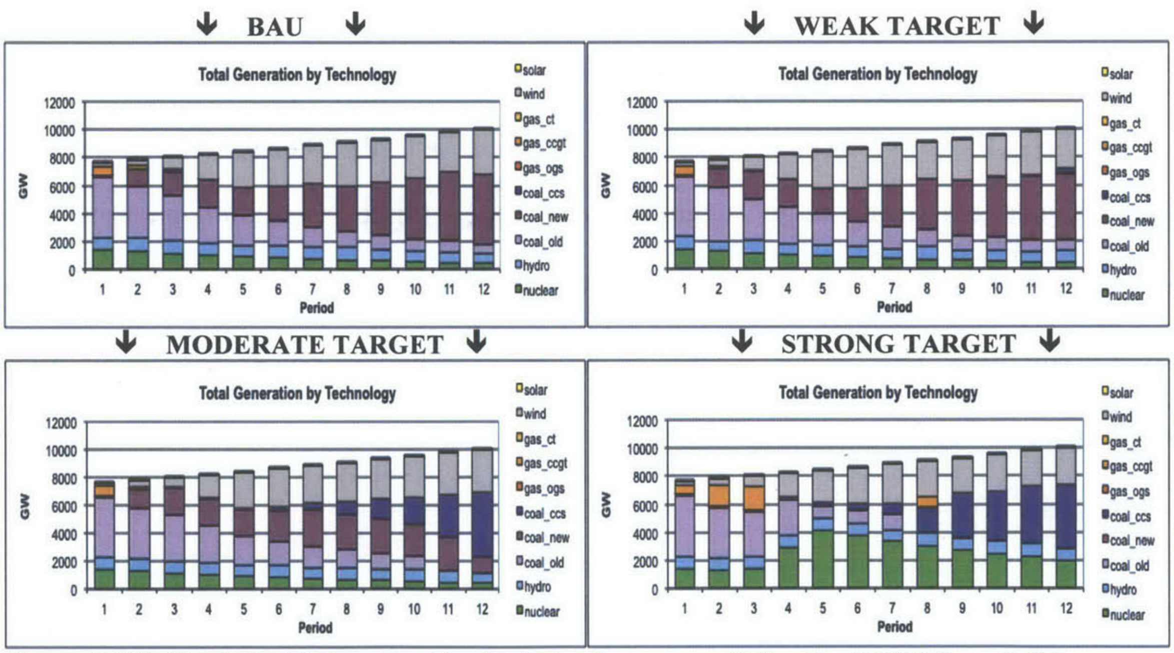


Figure 5-4 Optimal electricity generation by technology per period under BAU (a), weak (b), moderate (c), and strong (d) carbon targets

[9] Note the small difference between BAU and weak target emissions time profiles. The profiles track each other closely for the first 60-years of the planning horizon, but diverge in the terminal periods (years 65-100) of the problem.

## 5.2 Optimal Investment Strategy v. Endogenous Learning Dynamics

The next three numerical experiments explore in detail the technological learning dynamics introduced in the model. The first, described in this section, extends a comparison begun in Chapter 4.7 by studying the impact of the specific learning mechanism on the optimal capital and R&D investment strategy, and associated emissions profiles. Chapter 4.7 presents the reference version of the numerical model, which consists of both learning-by-doing (LBD) and learning-by-searching (LBS) for all emerging technology groups. It further compares the results to results from a version of the model with no learning dynamics incorporated. The present analysis provides a more detailed look at the impact of the individual learning-by-doing pathway versus learning-by-searching pathway on the optimal investment portfolio. As Chapter 3 describes, many modern electricity generation capacity planning and policy analysis models contain some form of learning-by-doing, but few incorporate endogenous learning-by-searching. The goal of this numerical experiment is to develop a refined sense of the specific impact of incorporating learning-by-searching into this type of a model. The comparison between the BAU reference model and the BAU no-learning model in Chapter 4.7 also highlighted the existing, but subtle, change in emissions profiles between the two. Unpacking the impact of LBD versus LBS in this change is also of interest.

Figure 5-5 shows R&D investment and installed capacities from scenarios with no learning, LBD only, LBS only, and both LBD and LBS under BAU. For ease of discussion, relevant results from Chapter 4.7 are replicated again below. First note that under a no-learning or LBD only scenario, there is no learning-by-searching mechanism included in the model and therefore no pathway to invest in R&D to reduce capital costs;

in these cases R&D investment are necessarily zero for all technologies. Results show no changes in installed capacities between the LBD only, LBS only, and LBD and LBS scenario; the only *slight* difference between these scenarios and the no-learning scenario is a small increase in wind installed capacity in Period 3 from the no-learning scenario. On the other hand, R&D investment in the LBS only scenario is nearly four times the R&D investment in the LBS and LBD scenario. The overall goal of this R&D investment is to reduce the capital cost of wind power as much as possible before large additions of new wind capacity, but this shows that in the presence of both LBD and LBS, less R&D investment is needed to achieve the same cost reductions. The reasoning behind this is that the model considers LBD a *relatively* "free" capital cost reduction mechanism—once a technology has an installed capacity base, it can learn [10]. Therefore, for the same installed capacity goals, the LBS only scenario, which cannot benefit from this additional free mechanism, needs more investment to reach the same target. Total system costs (NPV) from the four scenarios under BAU from least-cost to highest-cost are: $6.048 trillion (LBS and LBD), $6.081 trillion (LBD Only), $6.322 (LBS Only), and $6.461 trillion (No Learning). Such values suggest that results from current energy and policy analysis models without adequate representations of learning-by-searching may be over-estimating costs, possibly biasing cost-benefit analyses using these types of models.

[10] Note that learning-by-doing (LBD) is not *entirely* free, as it does still require investment in the actual capital.

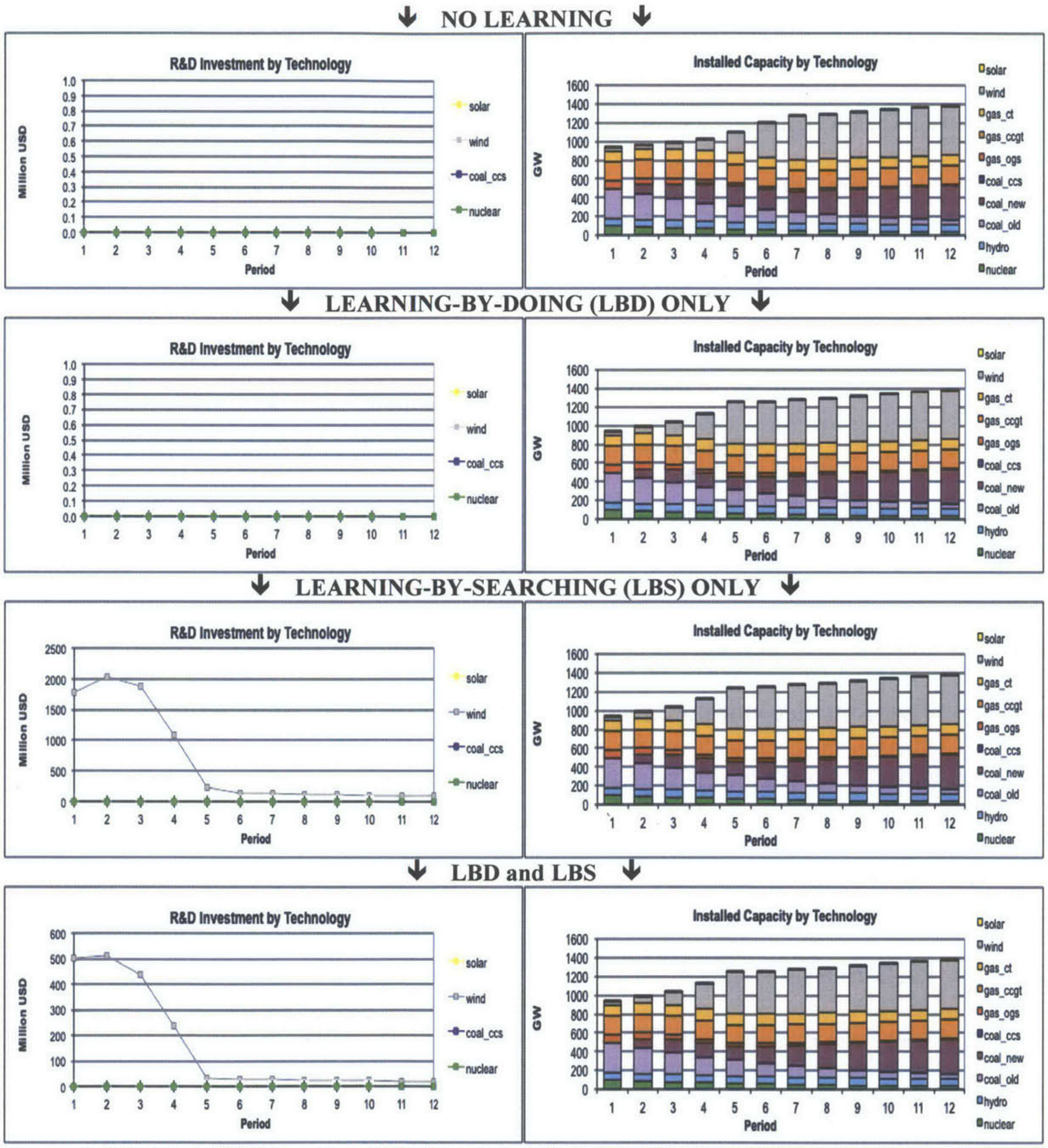


**Figure 5-5 Optimal R&D investments (left) and installed capacities (right) for various learning scenarios under BAU**

The impact of learning-by-doing and learning-by-searching on the optimal investment strategy is further explored under the 50% BAU moderate carbon target scenario to determine if the behaviors from the BAU scenario above persist. Results are shown in Figure 5-6 below. First, when a moderate carbon target is present, new capacity decisions are dominated by the goal to reach the cumulative carbon target and are insensitive to changes in the learning dynamics introduced in the model. This follows from the fact that LBS (as used in this model) does not reduce capital costs sufficiently to change the cost structure of the technologies and cause technology switching at this objective. Overall, the different learning pathways (or lack of learning pathways) afford an opportunity to meet the target at a lower (or higher) total system cost, but the physical system that needs to be reached and in place by the end of the planning horizon is constant under a specified cap. As discussed in Section 5.1 above, under the moderate target new capacity decisions are focused on wind power technology in the early periods and coal with CCS technology more gradually in the later periods.

The behavior of the R&D investment decisions track this capital investment requirement, and share the same general distinctions as in the BAU scenario above. Namely, R&D investment in wind is much higher in the LBS only scenario than when LBS and LBD are present, with a peak investment level approximately four times peak investment when both learning mechanisms are present (Figure 5-6). An increase under the LBS only scenario is also seen for coal with CCS technology when compared to the LBD and LBS scenario, showing once again that in the presence of "free" capital cost reduction, less active R&D investment is needed to allow the technology to be cost-competitive under this carbon cap. However, the increase in R&D investment level is less drastic under the LBS scenario in the coal with CCS case than in the case of wind. Peak R&D investment in coal with CCS reaches only approximately 150% of the investment level under both learning mechanisms.

The reasoning for this difference is three-fold. First, the difference can be attributed to the generally lesser amount of the technology required to meet this specific carbon target level (wind power continues to be the dominant technology required to meet this target). Second, the difference results from the specific characteristics of the technologies' learning dynamics. As Table 5-1 at the end of the chapter shows, coal with CCS has a much more inelastic (and thus slower for the same R&D level) learning-by-doing rate than wind; the result is that when LBD is taken away from wind technology learning, a larger amount must be recovered from the LBS pathway. The opposite is true with coal with CCS, an additional reason why only modest increases in coal with CCS R&D investment is seen in the LBD only scenario. Third, wind power enjoys a *relatively* large existing installed capacity base in the physical system, which allows it to take advantage of the LBD pathway more readily than coal with CCS, which starts out with a negligible amount of capacity. Thus, coal with CCS remains relatively "locked-out" of the LBD cost-reductions when compared to wind, which means that when the LBD pathway is cut off, coal with CCS has less to "lose" from it.

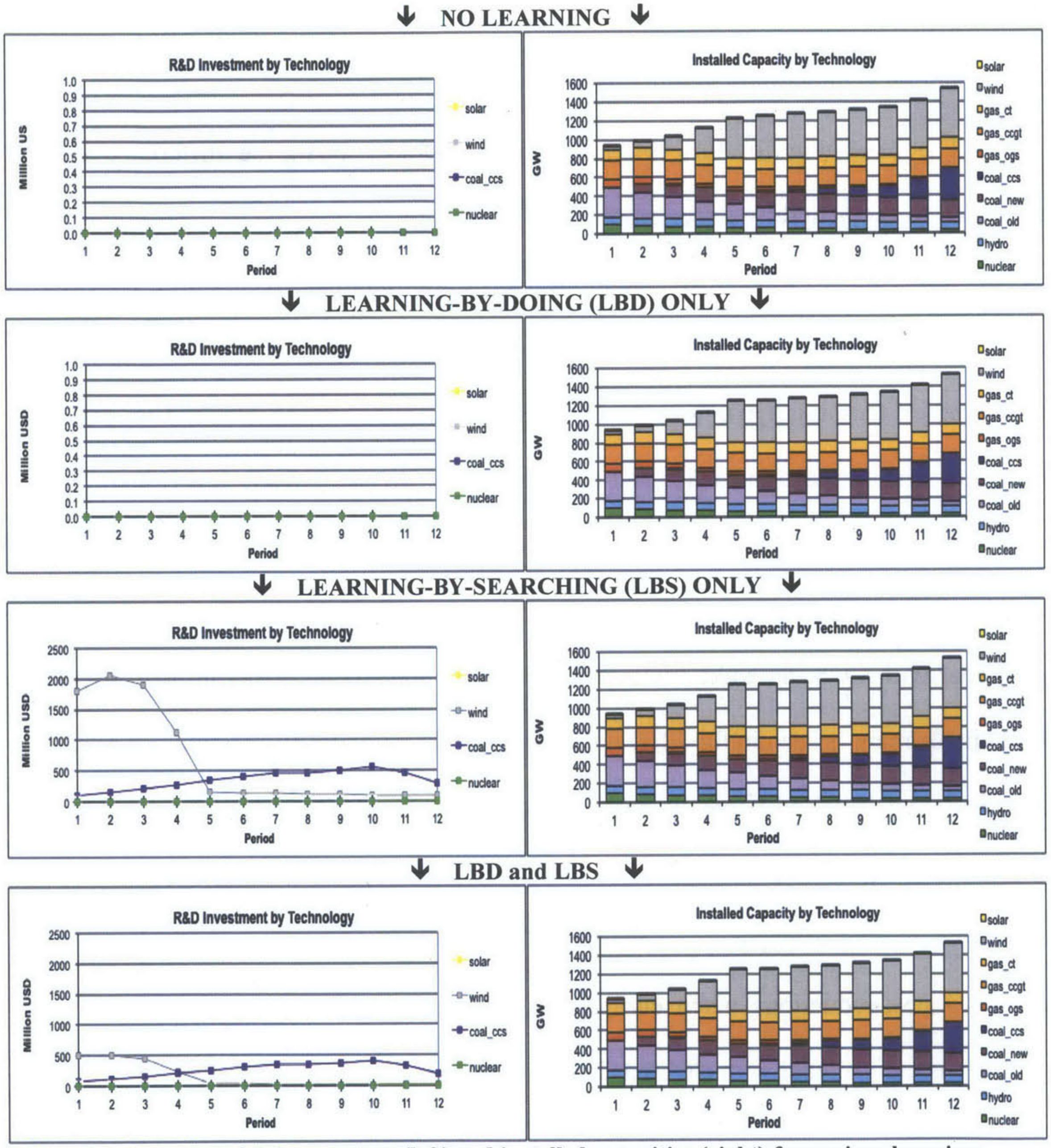


**Figure 5-6 Optimal R&D investments (left) and installed capacities (right) for various learning scenarios under a MODERATE (50% BAU) carbon target**

Next, Figure 5-7 below shows the per period emissions levels associated with the optimal investment strategies for the different learning scenarios. As a reminder, the comparison between the BAU reference model and the BAU no-learning model in Chapter 4.7 highlighted an existing, but subtle, change in emissions profiles between the two models. Here, the impact of LBD versus LBS in this change is unpacked and extended to the moderate carbon target scenario.

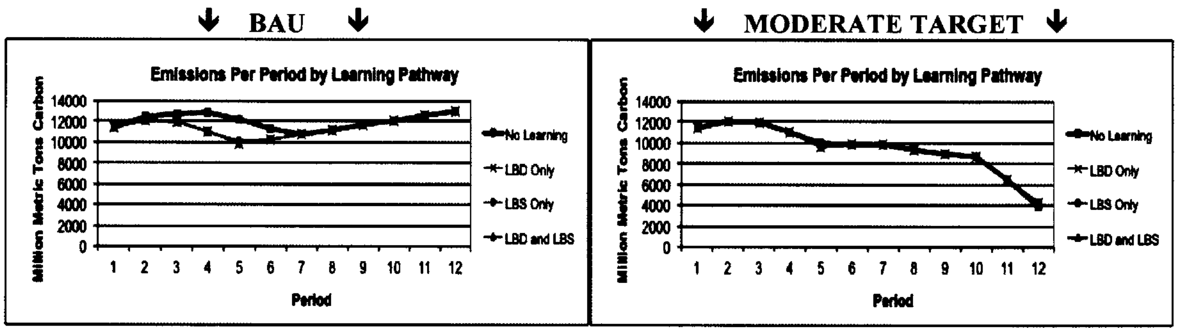

**Figure 5-7 Per period carbon emission trajectories for various learning scenarios under a BAU (a) and MODERATE (b) carbon target**

Figure 5-7a shows that under BAU per period emission profile differences are simply the result of a single learning mechanism being present in the model. The thicker black series in the graphs show the emission trajectory resulting from the no-learning scenario, whereas all other three series (LBD Only, LBS Only, and LBD and LBS) are identical. A discussion of why the dip in emissions is seen later, with no learning present, is provided in Chapter 4.7 above; this numerical experiment shows that the particular learning pathway does not affect how near-term emissions are allocated inter-temporally to meet the cumulative carbon target. Only in the case of no learning is the capacity mix significantly different enough to affect operation of, and thus emissions from, the physical system.

The same comparison is made under a more stringent carbon target in order to see if this behavior holds (Figure 5-7b). In fact, when a moderate carbon target is present, emission profile trajectories are also completely dominated by the goal to meet the cap and the learning pathway plays no role in emissions patterns. Thus, as Figure 5-7b shows, there is no change between the scenarios with different learning mechanisms. The result here is simply a change in total system cost across the different scenarios, with the order of least costly to most costly being: LBD and LBS, LBD Only, LBS only, and No Learning. This can be explained by the result discussed in Figure 5-6 above, where there was also no change in installed capacity mixes across the different learning scenarios. Once a physical system (and generation technologies) are in place, there is a single optimal operation plan for that system to meet demand.

Under a specific cumulative carbon target then, because the learning pathways are not sufficient to induce technology switching in capital investments, the focus becomes more on choosing the optimal combination of R&D investments for capital cost-reductions for the necessary technologies to be installed and operated to meet the cap. Under a carbon target, the result here suggests that there is a single optimal installed capacity trajectory, and by extension a single optimal emissions profile. In the next two numerical experiments, it is interesting to see that these behaviors hold.

## 5.3 Impact of Knowledge Stock Strength on Optimal Investment Strategy

A motivation for disaggregating the dynamics by which new knowledge is created from R&D effort (in contrast to earlier works that directly equate new knowledge to amount of R&D dollars invested) is the opportunity to study how characteristics of technology-specific knowledge stocks and dollars invested in R&D might differently affect the production of new knowledge, and therefore optimal R&D and capital investment strategies. As described in Chapter 3, recent empirical studies point to a variation between technologies on this effect, and the current literature (both empirical and modeling) is dominated by lumping the knowledge stock contribution into one category, or by using identical parameters across technologies to represent changes in knowledge over time. Thus, the next numerical experiment is a study of the optimal investment strategy given different values for the parameter $\phi$, the contribution of knowledge stock ($HEBACK_{t,g}$) to new knowledge ($NEWHEB_{t,g}$) in the innovation possibilities frontier (IPF) below—or the "strength" of effect from the accumulated knowledge stock:

$$NEWHEB_{t,g} = \alpha_g REBACK_{t,g}^{\beta} HEBACK_{t,g}^{\phi}.$$

In this experiment, the full endogenous learning model with emissions targets imposed is used. Sensitivity of the optimal R&D and generating capacity investment strategy on the value of $\phi$ for each emerging technology is tested separately, holding all other technology knowledge stock contributions at their reference model values. Results are first compared under the 50% BAU (moderate) carbon target scenario using a "high," "reference," and "low" value for $\phi$. In each scenario, the "high" value corresponds to a phi value of 0.8, the "medium" value to the reference value 0.54; and the "low" value to a phi value of 0.1. This range is chosen to retain the decreasing returns to scale Cobb-Douglas form of the reference IPF (i.e., the sum of elasticities less than 1) and diminishing returns to research (phi between 0 and 1). The reference value for the corresponding elasticity on R&D investment in the IPF is 0.1, allowing the sum of elasticities to range from 0.2—0.9. Figure 5-8 and Figure 5-10 show the resulting R&D investment and associated installed capacities from the wind and coal with CCS analyses, respectively. Supporting Figure 5-9 and Figure 5-11 show the capital cost trajectories and corresponding knowledge stock trajectories for the wind and coal with CCS analyses, respectively. Due to their insensitivity, full sets of figures for the nuclear and solar sensitivity analyses have been omitted (for brevity) but their results are also discussed below.

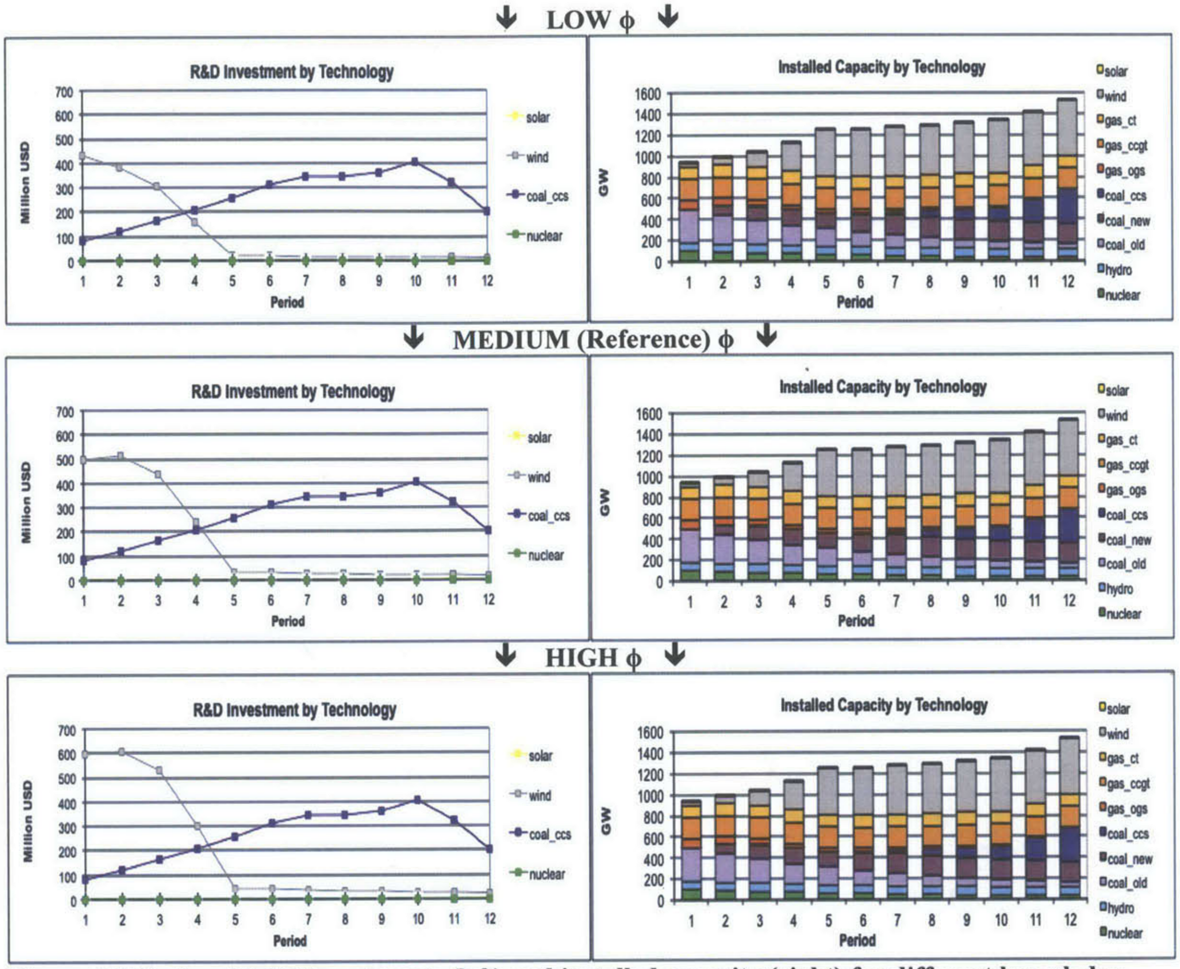


**Figure 5-8 Optimal R&D investments (left) and installed capacity (right) for different knowledge stock strengths for WIND technology under a MODERATE (50% BAU) carbon target**

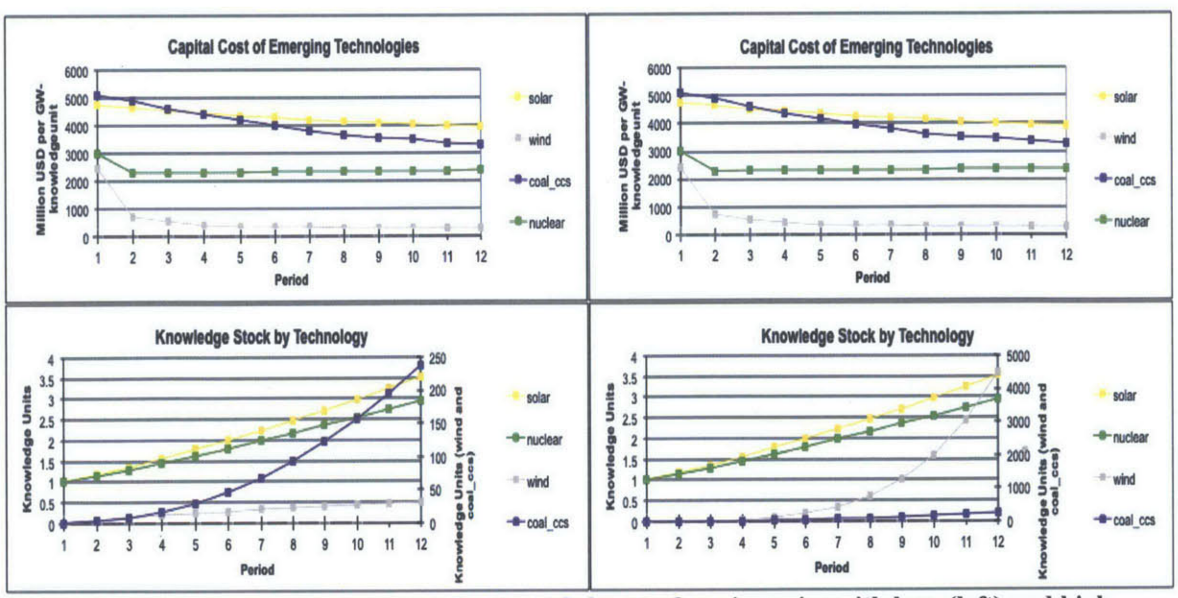


**Figure 5-9 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) WIND knowledge stock contribution strengths under a MODERATE (50% BAU) carbon target**

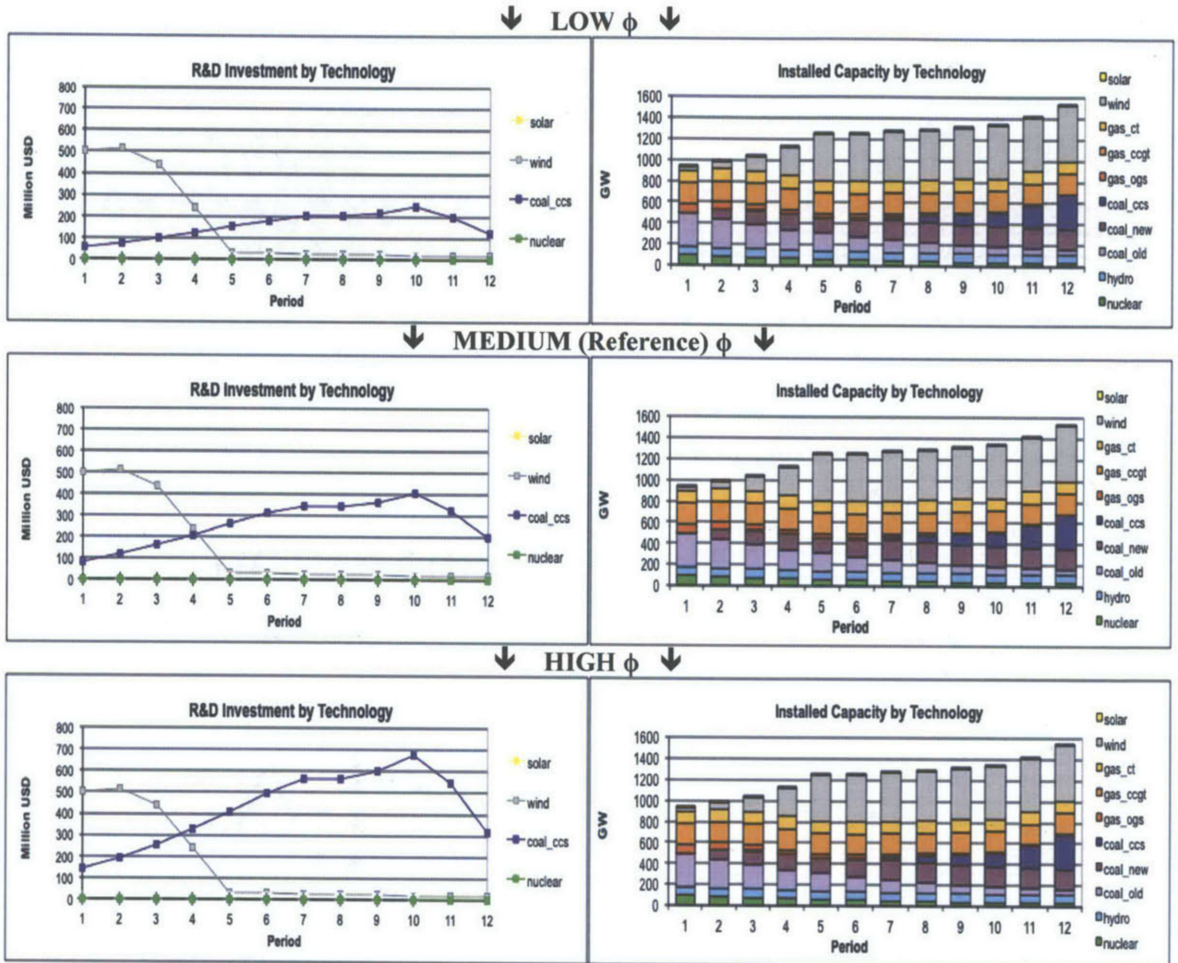


**Figure 5-10 Optimal R&D investments (left) and installed capacities (right) for different knowledge stock strengths for COAL WITH CCS under a MODERATE (50% BAU) carbon target**

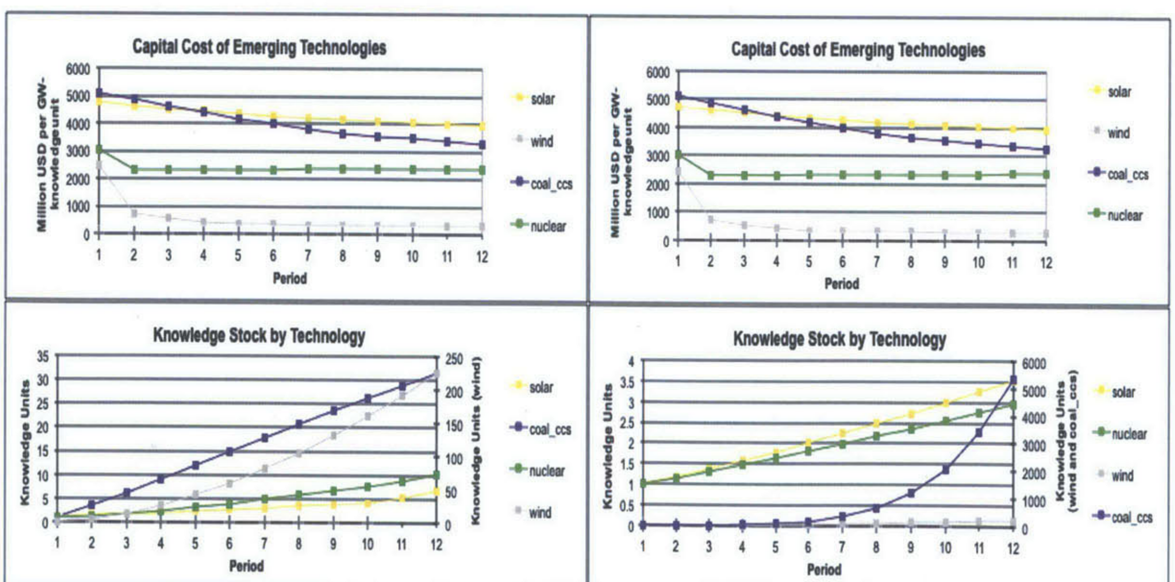


**Figure 5-11 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) COAL WITH CCS knowledge stock contribution strengths under a MODERATE (50% BAU) target**

Overall, sensitivity of the optimal R&D investment level on the strength of the knowledge stock effectiveness for new technology knowledge is modest. In the case of wind power, as $\phi$ increases, investment in R&D increases—from a peak investment level of approximately \$430 million under low $\phi$ to just over \$600 million under the highest $\phi$. However, neither installed capacity nor generation change. Additionally, increased wind R&D investments as a result of increased knowledge stock strength do not affect investment or new installation for the other emerging technology categories (i.e., coal with CCS R&D investments stay constant, nuclear and solar power investments are unaffected).

Each of these results is to be expected. First, the low resource availability factor for wind power means that it only provides a percentage of demand, before it is more economic for another technology to be installed and operated to meet a larger portion of the demand while still keeping emissions low. This creates an environment where wind fills a niche and it is difficult to bump it from this niche, limiting the value of R&D investment in this technology for minimizing total system costs. Additionally, as shown in Figure 5-9, although the knowledge stock for wind technology can even grow exponentially (at the highest $\phi$ level), the change in actual capital costs is relatively insignificant when considering how inexpensive wind technology already is compared to the other technologies (unnoticeable on the graph, the difference is between approximately \$357 million/GW-knowledge unit for $\phi$ = 0.1 to \$209 million/GW-knowledge unit for the highest $\phi$ = 0.8). Relative to its starting capital cost of \$2438 million/GW-knowledge unit, the percentage reduction by the end of the planning horizon is 85% for $\phi$ = 0.1 compared to 91% for $\phi$ = 0.8. The next cheapest technology in terms of final capital cost is nuclear power at $2472 million/GW-knowledge unit. Considering its zero fuel cost and low other variable cost, wind power therefore is simply limited here by its resource availability and imposed capital installations rate of change constraints (otherwise it would certainty dominate the entire physical system at these low costs).

Second, additional R&D investment in wind technology is independent of other technology R&D decisions because knowledge creation for one technology group is not linked to knowledge creation for another technology group in the current modeling framework; knowledge accumulation and new knowledge creation are limited to "within technology" dynamics. Clearly, the possibility that knowledge creation in one technology can affect opportunities to generate new knowledge in another technology group is very real. However, for the purposes of introducing the new modeling framework and keeping it tractable, solely "within technology" dynamics are considered.

Third, as shown in Section 5.2 above, the specific carbon target dominates the generating capital deployment (installment) plan. The fact that the optimal installed capacities are insensitive to changes in the strength of the knowledge stocks here confirms this finding, and adds to the notion that the role of learning in this problem as formulated, is relatively weak—enough to reduce overall system costs to meet a specified cumulative carbon target and installation plan, but not strong enough to induce technology switching.

Figure 5-10 shows that as $\phi$ increases for coal with CCS, R&D investment increases substantially. The same general trajectories exist for R&D and generating capacity investments across levels of phi: a gradual increase in R&D investment over time, peaking at approximately Period 10, and gradual addition of new coal with CCS capacity with an emphasis on the later periods when meeting the cumulative carbon cap is more imminent. Like the wind case above, the actual generation deployment plan does not change across coal with CCS phi levels either. The difference across levels simply reflects the relationship between total R&D invested and a less effective knowledge stock: a peak investment of approximately \$250 million for $\phi = 0.1$ to \$675 million for $\phi = 0.8$.

Associated capital cost trajectories and knowledge stock trajectories in the low $\phi$ and high $\phi$ case are given in Figure 5-11, but in contrast to the wind case above, they show the greater cost changes for coal with CCS when $\phi$ increases, and more drastic increases in knowledge stock. For the lowest level of $\phi = 0.1$, the capital cost for coal with CCS is approximately \$3278 million per GW-knowledge unit; for the highest level $\phi = 0.8$, the capital cost declines to \$2817 million per GW-knowledge unit—a total of 9% additional reduction from the original capital cost of \$5099 million per GW-knowledge unit for stronger knowledge stock. Likewise, the cumulative knowledge stock witnesses 5361-fold increase when $\phi = 0.8$, compared with a 32-fold increase when $\phi = 0.1$. In contrast, the wind knowledge stock in the wind analysis above only saw a 4512-fold increase at the highest $\phi = 0.8$ level and a 31-fold increase at the lowest $\phi = 0.1$ level.

This behavior for coal with CCS in response to changes in phi can be explained by considering the necessary role of coal with CCS in the deployment plan to meet the moderate cumulative carbon target, and the lack of an existing installed capacity base to begin with. The capital cost (*CAPC*) for a technology, *g*, at time, *t,* shown again below, remains a function of both the technology's cumulative knowledge stock (*HEBACK*—

"learning-by-searching") and the technology's cumulative installed capacity base (*CAPACITY*—"learning-by-doing").

$$CAPC_{t,g} = \frac{CAPC_{0,g}}{(CAPACITY_{t,g}^{\eta1_g})(HEBACK_{t,g}^{\eta2_g})}$$

With wind technology, the existing installed base is already relatively sizable (when compared to the negligible coal with CCS the system begins with). As resource availability and installed capacity rate of change constraints become active, coal with CCS technology has more room to grow within the system, and is needed to meet the cumulative cap. Due to limits on the maximum amount of additional capacity the system can handle between one period and the next, and the significantly lower LBD and LBS elasticities ($\eta1$ and $\eta2$, respectively) in the capital cost equation for coal with CCS than wind, the focus is placed on growing the coal with CCS cumulative knowledge stock quickly in order to reduce costs as much as possible. Additional R&D investment provides the mechanism for doing so, by feeding the innovation possibilities frontier. The above result is a nice example of how constraints in the operation of the electric power system and the characteristics of individual technologies can affect R&D investment and technological learning differently for two different technologies with the same level of effectiveness for how the knowledge stock contributes to new knowledge.

Results from the $\phi$ sensitivity analysis for nuclear power and solar power confirm a pattern that has emerged throughout the study. In the case of a moderate carbon cap, neither technology is part of the capital deployment plan. Varying the strength of the knowledge stock contribution to the creation of new knowledge (and ultimately opportunity for capital cost reduction) does not change this result in the case of either technology. As phi varies from 0.1 to 0.8, neither R&D investments nor the need for capital investments appear. Likewise, changes in the opportunity to generate new knowledge do not affect opportunities or decisions made for any of the other technologies.

Figure 5-12 and Figure 5-13 show the corresponding capital costs for the emerging technologies in the case of a low and high phi level for both nuclear and solar.

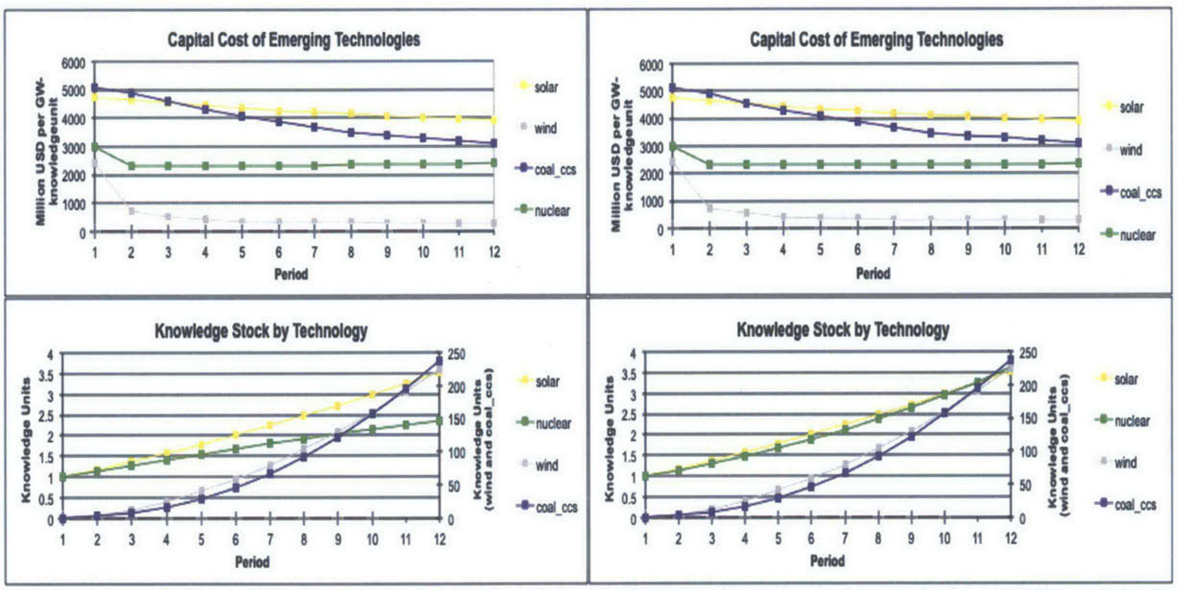


**Figure 5-12 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) NUCLEAR knowledge stock contribution strengths under a MODERATE (50% BAU) carbon target**

Nuclear technology remains too expensive as a combined package of fixed capital and variable/fuel costs to be competitive at this carbon cap. Its existing installed capacity base allows it to use LBD to reduce capital costs initially, but its eventual lack of need for this carbon target actually causes an implicit "forgetting" mechanism to kick-in and after Period 2 capital costs for nuclear technology actually increase gradually. This increase is also due to the fact that older nuclear plants retire from the system, causing the installed capacity base to decrease. Overall, the nuclear knowledge stock reaches a higher cumulative value under a stronger knowledge stock contribution level, but remains limited due to the lack of emphasis on the technology and R&D investments.

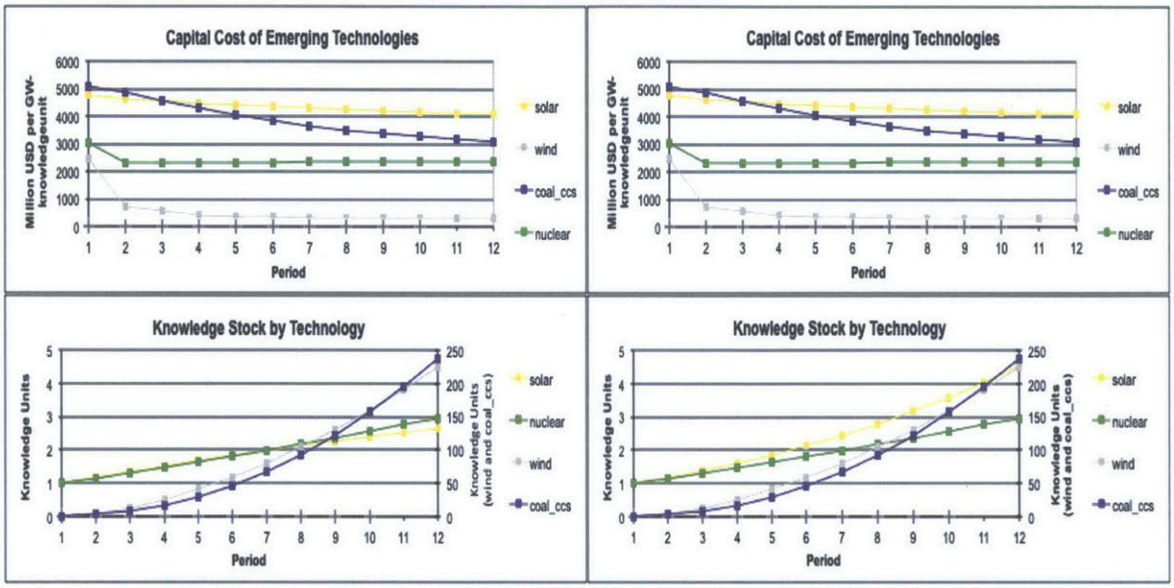


**Figure 5-13 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) SOLAR knowledge stock contribution strengths under a MODERATE (50% BAU) carbon target**

Solar technology exhibits a similar pattern, with no R&D investments and no new capacity additions under the moderate carbon cap across all possible values for phi. Like nuclear power, it is not part of the deployment plan for this cap level; a combination of its high initial capital cost and limited resource availability rate do not allow it to play a role in meeting the current goal. In contrast to nuclear power, solar capital costs continue to decrease over time because of its much higher LBD elasticity (0.41504 compared to 0.05889 for nuclear) and also the lack of retirements imposed in the modeling framework, keeping installed capacity constant over time. Thus, as the knowledge stock grows, capital costs continue to decrease.

Overall, the results of the nuclear and solar phi sensitivity analyses confirm that the cumulative carbon cap and corresponding deployment plan dictate how R&D investments change. They show that the emerging technology learning pathways and parameters used in the model are relatively insufficient for changing deployment decisions, especially when considering the starting values for capital costs. Even the strongest possible knowledge stock contribution rate in this case was not enough to cause nuclear to trade places in cost-competitiveness with coal with CCS. For solar, its limited resource availability, high initial capital cost, and low initial existing capital stock interact to keep it "locked" out of achieving swift cost reductions in the model, particularly when a more competitive non-emitting technology such as wind power is available.

Finally, Figure 5-14 shows summary results from a full sensitivity analysis of phi levels on peak R&D investment levels for all technology groups under each of the three carbon target stringencies. Associated installed capacities for each of the carbon targets is included for discussion. Peak R&D investment behaviors correspond to the discussions above. Under all three carbon targets, as phi increases, peak R&D investments increase monotonically, at a rate influenced by its relative need to meet the cumulative carbon target, initial installed capacity, and individual learning-by-doing and learning-by-searching elasticities.

Under the weak target, both wind and coal with CCS technology peak R&D investment increases gradually over phi. New wind capacity is the focus under this cumulative carbon target, but its relatively large existing installed capacity base, maximum capacity constraint, and relatively easy ability to "learn" (high LBD and LBS rates) keeps its R&D investment low. Coal with CCS in this scenario only plays a small role, keeping its R&D investment low as well.

Under a more aggressive moderate carbon target, the behavior of wind R&D investment does not change as it is already doing as much as it is capable of (and is optimal to do), but coal with CCS R&D peak investment grows over phi at a faster rate than under the weak target. This is explained by coal with CCS technology's increased role in the capital deployment plan under the moderate target, its small initial existing base, and its relatively lower LBD and LBS rates. As explained above, coal with CCS technology's small existing base does not allow it to take advantage of the learning-by-doing pathway as much, so the dominant pathway for initial capital cost reduction for coal with CCS is through R&D investment to grow the cumulative knowledge stock. As the objective is to meet total system needs at least cost, the faster growth for peak R&D investment over phi values is simply a result of having the opportunity to bring the capital cost of this scenario-required technology down more quickly. Investing more up front is less costly than investing less and paying higher discounted costs later, or choosing another technology.

Finally, under the strong target, the behaviors of wind and coal with CCS R&D investment are not altered from the moderate target, but the nuclear technology peak R&D investment is seen. The general behavior is the same as the other technologies and peak R&D investment increases monotonically over phi. However, although the deployment plan shows nuclear power to have a similarly strong role as coal with CCS in meeting the stringent cumulative carbon cap, the rate at which peak R&D investment increases over phi is lower than coal with CCS. This can be explained by nuclear power's much larger initial existing capital stock, which allows nuclear technology to take advantage of the "free" learning-by-doing pathway as well as the learning-by-searching pathway towards capital cost reductions. A higher phi in the case of nuclear does not create the same incentive for ramping up R&D investment as it did for coal with CCS technology.

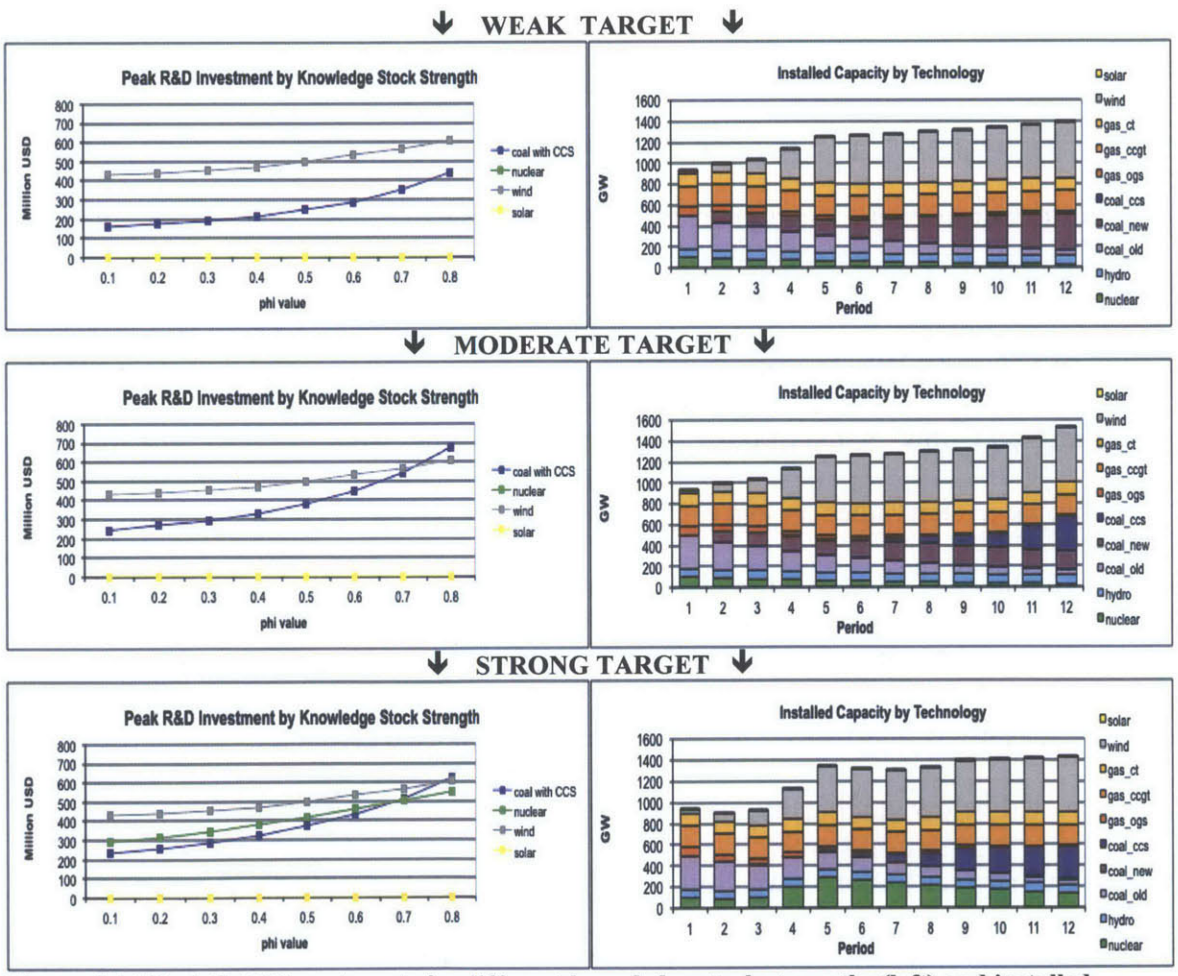


**Figure 5-14 Peak R&D investments for different knowledge stock strengths (left) and installed capacities (right) under three carbon targets**

## 5.4 Impact of R&D Program Efficiency on Optimal Investment Strategy

The second parameter, β, of the innovation possibilities frontier represents the contribution of R&D dollars invested in the production of new knowledge, which can be considered an "efficiency" for the investment. The theoretical, empirical, and modeling literature on innovation and the economics of technological change is replete with many references to the uncertainty inherent in the returns to R&D investment; this third experiment is devoted to a sensitivity analysis on this parameter. In doing so, it allows an initial investigation into the potential effect of this uncertainty on optimal R&D investment and emissions policies.

The full endogenous learning model with emissions targets imposed is again used, and this section uses the same procedure as in the previous experiment of varying each technology category β parameter separately, while holding other technologies at their reference values (0.10). The parameter β is varied for each technology using a "high," "medium," and "low" value of 0.02, 0.10 (reference value), and 0.40, respectively. This range for parameter values are once again chosen to retain the decreasing returns to scale of the reference IPF, and the diminishing returns characteristic for energy research (beta is between 0 and 1). Results between the scenarios are compared. For brevity, the results from the sensitivity analyses on the wind and coal with CCS technology IPF β parameter are presented below graphically. Due to the lack of response under the moderate carbon target with respect to their own R&D investment, their own new capacity addition, or their impact on other technologies' R&D investments, capacity additions, or generation, the nuclear and solar IPF β parameter sensitivity results are discussed briefly afterwards.

Figure 5-15 shows that as the efficiency of wind R&D increases from the low $\beta = 0.02$ to high $\beta = 0.40$, R&D investment grows (approximately 20 times, at the peak investment level). However, this experiment again shows the independence of the different technology's learning pathways. Increased R&D investment in wind affects neither R&D investments nor new capacity additions for any of the other technologies; coal with CCS technology plays a moderate role under this carbon target both in terms of R&D investments and new capacity, but its own investment strategy stays constant throughout changes in the efficiency of the wind technology R&D program. Likewise, new own capacity additions for wind do not change throughout different R&D investment strategies. This result is in line with the strong role of the carbon target in designing the overall capital deployment plan, and the total system cost-reduction role of the learning-pathways in this problem, rather than a technology-switching role. Finally, as expected due to the lack of change in capacity plans, the emissions time profile experiences no change throughout the technology IPF sensitivity analyses in this experiment.

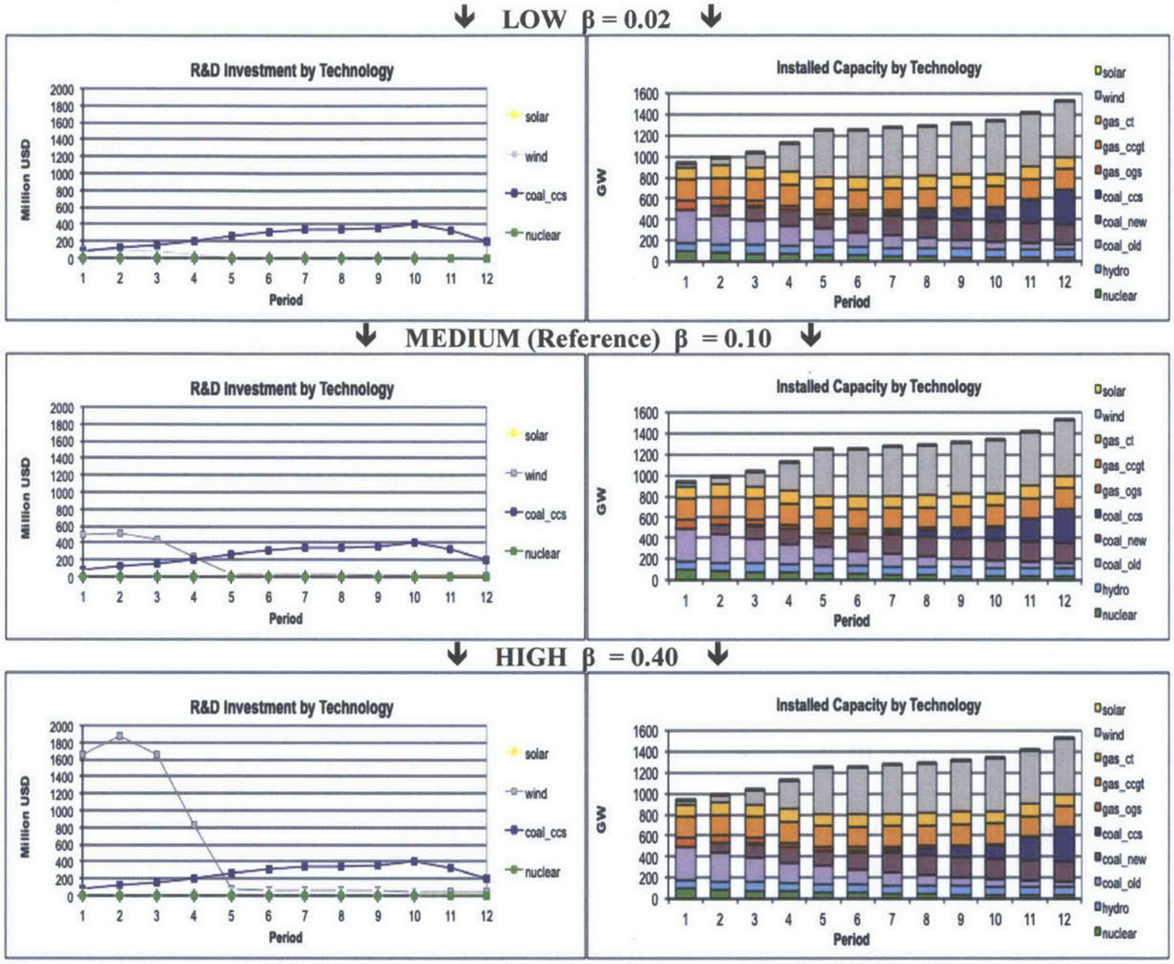


**Figure 5-15 Optimal R&D investments (left) and installed capacities (right) for different R&D program efficiencies for WIND technology under a MODERATE (50% BAU) carbon target.**

Figure 5-16 presents the capital cost and corresponding knowledge stock trajectories for coal with CCS under the low and high IPF beta scenarios. As shown, the knowledge stock for wind investment responds considerably to the high R&D program efficiency, and at its peak, reaches a level approximately 18 times greater than the low-level peak (note the difference in scales across the two scenario graphs). This is expected given the much larger base values for R&D investment in the innovation possibilities frontier function, compared with the knowledge stocks in the previous experiment that were all initialized at 1.0.

The more telling change is seen in the final capital cost reductions witnessed from this change in R&D program efficiency and R&D investment level (Figure 5-17). The overall actual capital cost reduction is sizable, in the range of 90% from the initial capital cost of $2438 million per GW-knowledge unit. As shown however, the difference in the capital cost reduction is quite small across the different levels of R&D program efficiency—from $300 million per GW-knowledge unit to $222 million per GW-knowledge unit at the end of the problem horizon. This corresponds to an additional 3% reduction from the original capital cost. Such small cost impacts of the additional R&D program efficiency helps explains why while total system cost is reduced from this additional upfront R&D investment (from 6.369 to 6.345 trillion NPV), technology switching through new capacity additions are not favored to meet the current cumulative carbon target.

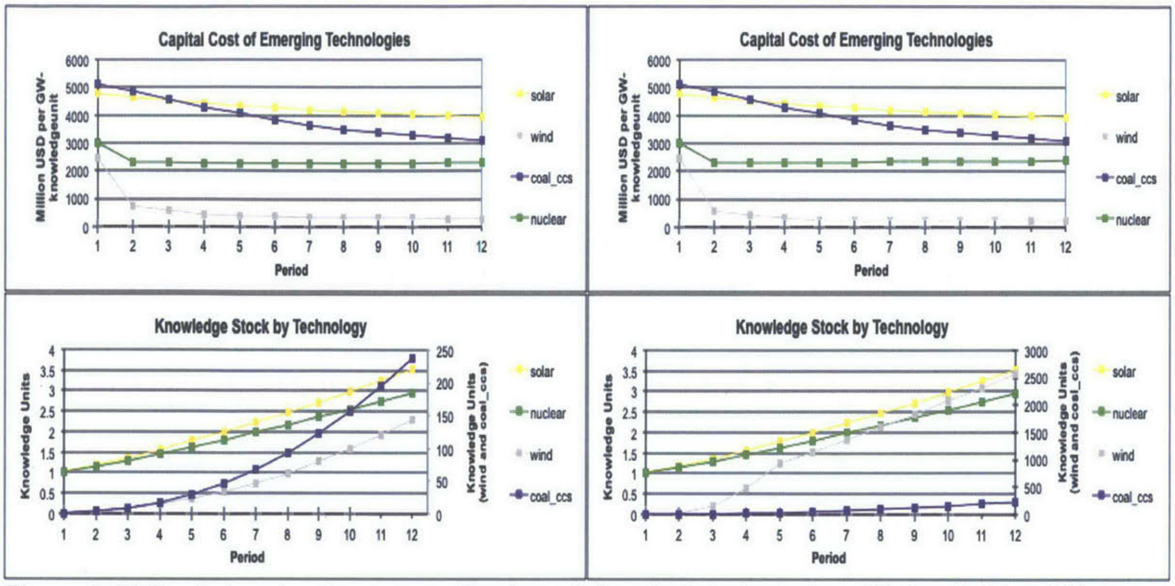


**Figure 5-16 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) WIND R&D investment efficiency under a MODERATE (50% BAU) carbon target**

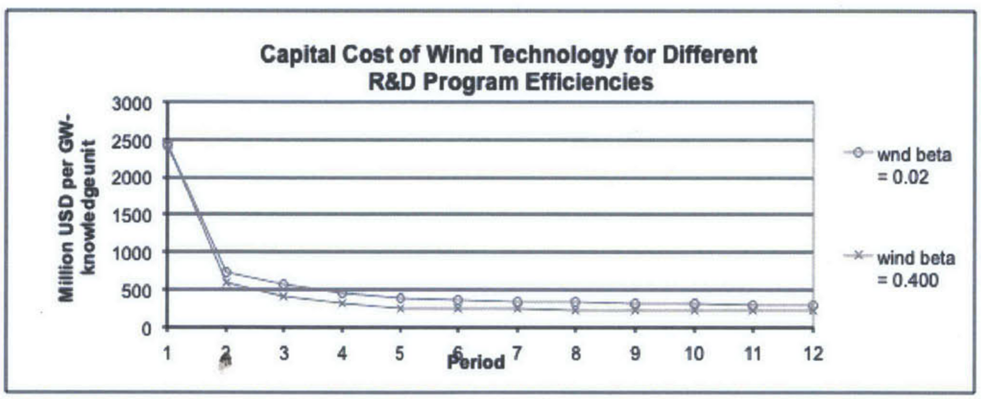


**Figure 5-17 Comparison of capital cost trajectories with low (o) and high (x) WIND R&D investment efficiency under a MODERATE (50% BAU) carbon target**

Figure 5-18 shows results from the coal with CCS R&D program efficiency sensitivity analysis. As R&D efficiency grows, investment grows substantially (approximately 25 fold, at the peak investment level in Period 10). Once again, R&D investment for other technologies is unaffected, as are new capacity additions for any technology, including coal with CCS.

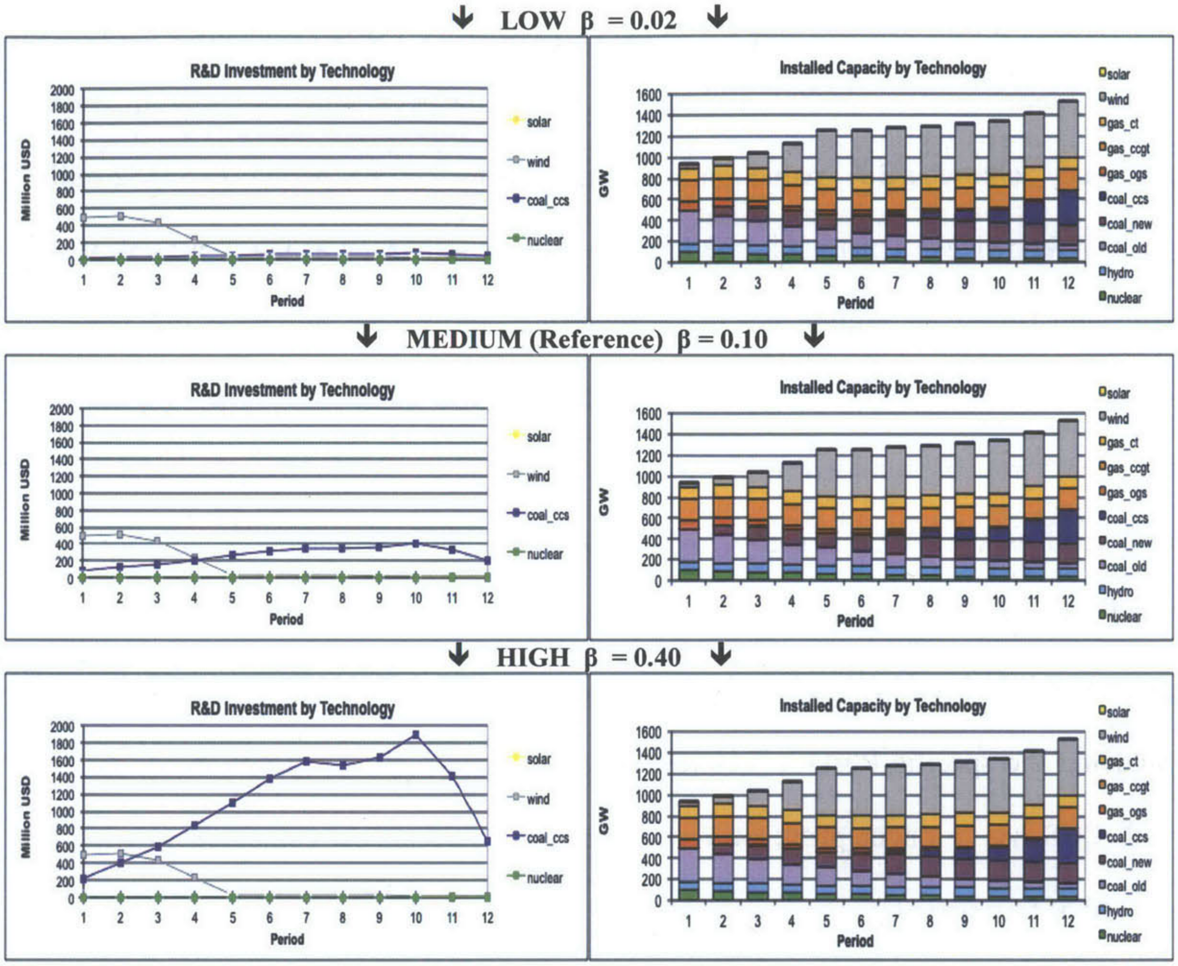


**Figure 5-18 Optimal R&D investments (left) and installed capacities (right) for different R&D program efficiencies for COAL WITH CCS technology under a MODERATE (50% BAU) carbon target**

Figure 5-19 below shows the corresponding capital cost and knowledge stock trajectories for the emerging technologies under the cases when coal with CCS R&D investment efficiency is low and high. The results show the relatively fast rate of knowledge stock increase for coal with CCS under high investment efficiency and the analogous relatively fast rate of decline for the capital costs for coal with CCS (notice the swifter rate by which coal with CCS approaches the nuclear technology capital cost by the final period). Figure 5-20 emphasizes the capital cost trajectory of coal with CCS individually for the low and high investment efficiencies for easier comparison. From the initial capital cost of $5099 million per GW-knowledge unit, the low investment efficiency achieves a 38% reduction in capital costs by the final period (to $3152 million per GW-knowledge unit) while the high investment efficiency achieves a total of 45% reduction (to $2779 million per GW-knowledge unit). This additional 7% reduction contrasts with the small 3% additional reduction that wind technology capital costs received through increased R&D program efficiency. As in the first and second numerical experiment, this can be explained by the lower resource availability rate for wind and the greater focus on baseload technologies with large emission reduction potentials, for R&D investment and deployment under more stringent carbon targets. Studying the specific R&D trajectories of wind versus coal with CCS shows that coal with CCS has a longer phase of very large R&D investments compared to wind (six instead of four periods).

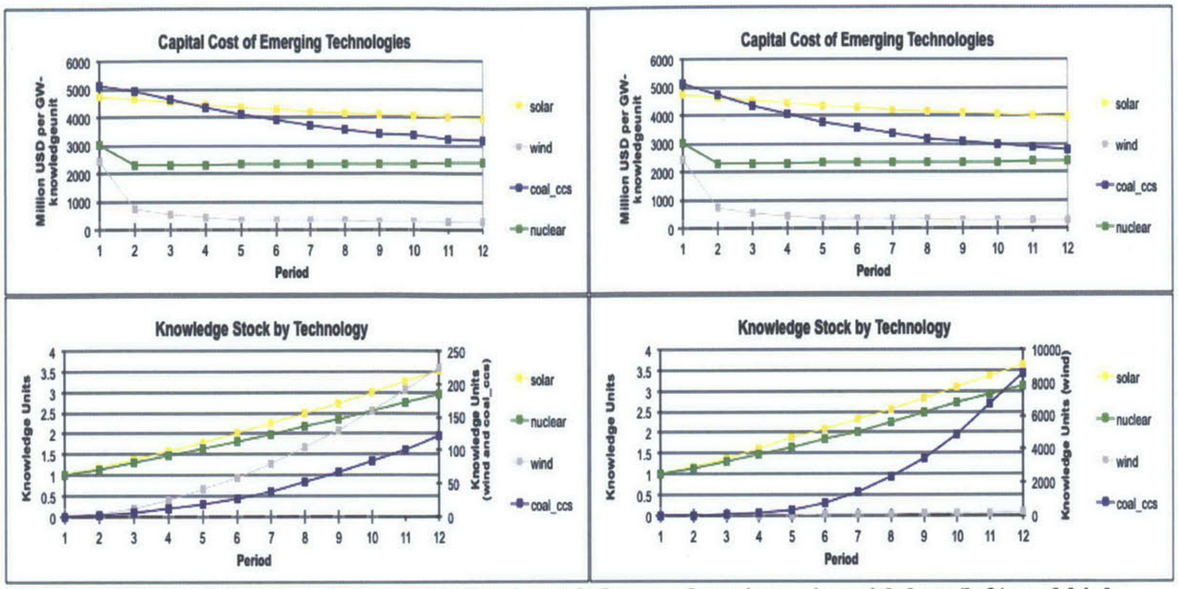


**Figure 5-19 Capital cost and corresponding knowledge stock trajectories with low (left) and high (right) COAL WITH CCS R&D investment efficiency under a MODERATE (50% BAU) carbon target**

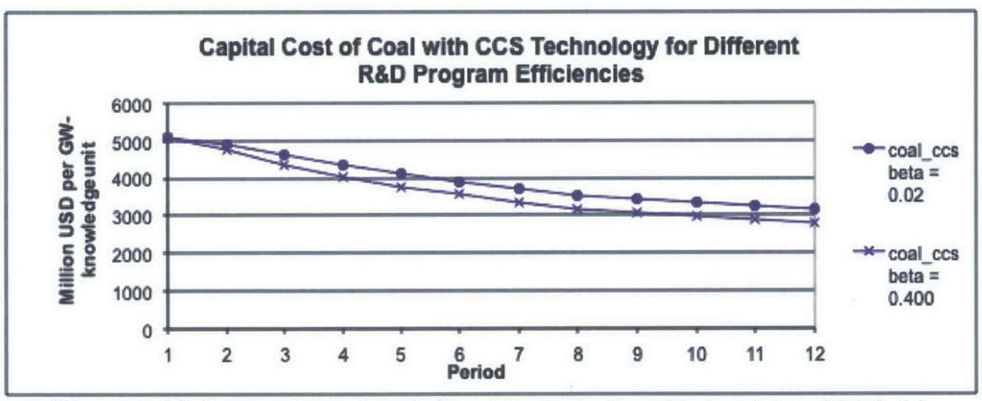


**Figure 5-20 Comparison of capital cost trajectories with low (o) and high (x) COAL WITH CCS R&D investment efficiency under a MODERATE (50% BAU) carbon target**

Under this carbon target and corresponding capital deployment plan, both nuclear technology and solar technology again play no role with respect to R&D investment or new capacity additions. This fact remains constant irrespective of these technologies' R&D program effectiveness. Even when the potential efficiency of R&D investments to contribute to capital cost reductions are almost unrealistically high (at the highest levels of beta in the IPF), there is no change in the investment strategy. Graphical results for these sensitivity analyses are not presented; final results are the same as those shown for nuclear and solar power analyses under the previous experiment on the IPF phi parameter. For nuclear power technology, it remains too expensive as a combined package of fixed capital and variable/fuel costs to be competitive at this carbon cap. For solar power technology, the story is the same—its capital cost simply remains too high for it to be economic at this target stringency when wind power or another technology can meet demand. This lack of change in their own investment strategies also extends to a lack of any effect on other technologies' investment strategies or learning pathways.

Finally, Figure 5-21 shows summary results from a full sensitivity analysis of beta levels on peak R&D investment levels for all technology groups under each of the three carbon target stringencies. The main sensitivity analysis was performed on nine levels for beta ranging from 0.02—0.18, around the reference value of 0.1. For additional study, a beta level of 0.40 at the end of the range of possible values but that still ensured the original decreasing returns to scale IPF formulation is also included and presented below. Associated installed capacities for each of the carbon targets are again included for discussion purposes. Results generally follow those from the previous sensitivity analysis on knowledge stock effects, with a few exceptions.

First, under all three carbon targets, as beta increases, peak R&D investments again increase monotonically at a rate influenced by the technology's relative need to meet the cumulative carbon target and its installed capacity. Note that the rates of increase are more linear at this small range of elasticity levels than the comparable graphs for the phi sensitivity analysis, which explored a much greater range. Under the weak carbon target, the focus on wind power in the capital deployment plan matches the higher rate of R&D investment increase for wind. This differs from coal with CCS technology, which plays a larger role in the deployment plan in later periods. A higher beta parameter means that for one dollar of R&D spent, a larger quantity of knowledge is produced, thus bringing capital costs of this required technology down even faster. Under the moderate target, the shift towards more coal with CCS helps balance the focus towards a combination of the two technologies, matching the smaller difference seen in the rate of R&D investment between the two technologies' growth across beta levels. Lastly, under the strong carbon target for which nuclear power plays a role in the investment strategy, the smaller difference between rates of R&D increase across beta levels is maintained as all three technologies are required to meet this more stringent cap.

However, peak R&D investment for nuclear power under a strong carbon target displays a different pattern across levels of R&D program efficiency than level of knowledge stock effectiveness (phi). Note that at the highest levels of beta, nuclear power peak R&D investment exceeds wind and coal with CCS peak R&D investment (coal with CCS R&D investment is hidden behind the wind data point), while at the lower beta levels, wind dominates. In the case of the phi sensitivity analysis, the nuclear power R&D investment path remained below wind and above coal with CCS at the lower phi levels, and coal with CCS dominated at the highest phi level.

The behavior here can be explained by a combination of 1) the fact that nuclear power has a relatively large existing installed capacity base, whereas coal with CCS and wind do not, 2) the necessity of nuclear power in the current deployment plan, and 3) the general formulation of the IPF and two-factor learning curve (2FLC). Because nuclear power technology has a large existing capital base and will have additional capacity additions under the strong target, there is an incentive to take full advantage of both its LBD and LBS pathways for capital cost reduction. In order to do so, the cumulative knowledge stock ought also to be large; the main pathway to achieve this is through more R&D investment in the IPF. Hence, the extra focus on nuclear at these high efficiency levels is expected. Coal with CCS technology, for example, does not display the same behavior at these high efficiency levels because the lack of an existing coal with CCS capital base does not allow it to benefit as much from simultaneous LBD and LBS cost-reduction pathways. Higher beta levels still spur additional R&D investments for all three technologies, but the additional incentive to invest even more in nuclear at the highest levels is unique to nuclear in this scenario.

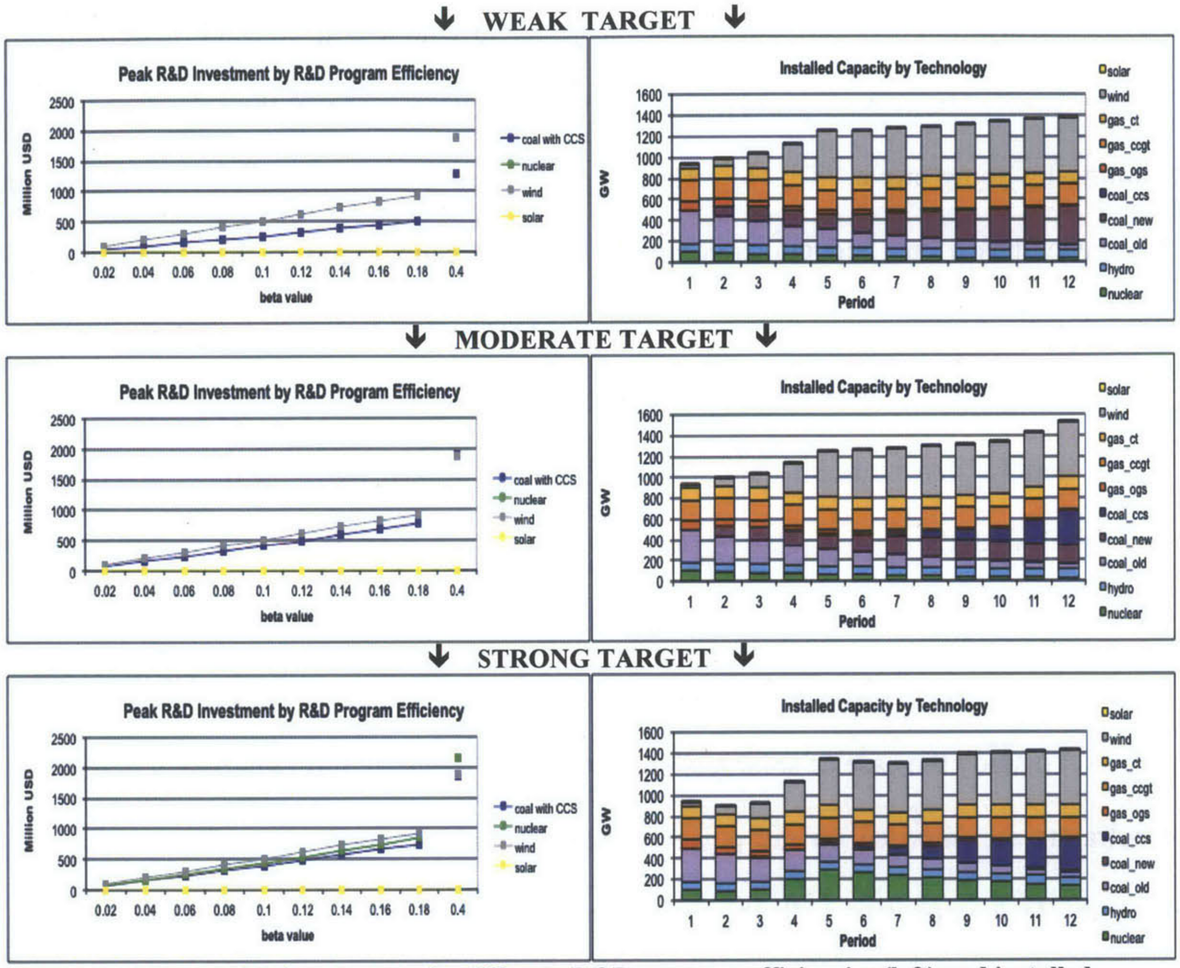


**Figure 5-21 Peak R&D investments for different R&D program efficiencies (left) and installed capacities (right) under three carbon targets**

## 5.5 The Case for Solar Technology

In the numerical experiments above, the capital cost of solar technology remained too high for it to be cost competitive with other available technologies to meet electricity demand at the carbon stringencies studied. The absence of solar power in the optimal investment strategy in these experiments is driven by three key interrelated factors. First, the initial capital cost of solar technology used in the analysis is very high, far above that for wind technology, which becomes the dominant intermittent renewable technology chosen for R&D and new capacity above. Thus, solar has a greater distance to travel "down the learning-by-searching curve" in order to compete with wind. Second, the initial capacity (cumulative experience) of solar is very low and it is thus also high on the learning-by-doing curve. This low starting point does not allow it to take advantage of experience-based cost reductions compared to other technologies in the model. Third, solar power generates only in specific demand slices, with peak generation displaced a few hours from when solar radiation is most intense. Thus, solar is a "niche" technology in the model (even more so than wind); it is quite limited by its resource availability given the system's current relative inability to store its generated power for use during off-solar-peak times. All three of these characteristics work together to keep solar technology at a competitive disadvantage.

To study the case of solar technology in more detail, in this experiment additional constraints are imposed on the power system to find the conditions where solar does become cost-competitive with the other available technologies. In this analysis, wind technology does not learn (neither via LBD nor LBS) (e.g., it has already reached a learning "limit"), new nuclear installations are not allowed (e.g., for political reasons), and coal with CCS is severely constrained and can only reach a max capacity of ten percent of peak demand (e.g., there are not enough viable or otherwise acceptable storage sites available).

Figure 5-22 shows results from this analysis under a business as usual scenario for carbon target stringency. Solar R&D investments displace wind in the earlier BAU scenario (Section 5.1) when wind continued to learn. In terms of installed capacities, however, solar installations only displace a small portion of new wind installations (and generation). Because solar only operates in specific demand slices, the system needs another available technology to fill in to meet demand fully. In this constrained system, wind (even non-learning wind), is the next most competitive technology. Due to the non-learning nature of wind technology in this case, small amounts of coal with CCS R&D investment and new capacity additions also appear under the BAU scenario; this is different from the original reference scenario, when coal with CCS did not appear until there was a carbon cap to meet. In this case, though it is capacity constrained, coal with CCS continues to learn, and this makes it an attractive option for R&D investment and capital cost reduction to minimize total system costs.

The emissions time profile of the BAU scenario tells a similar story to that of the original reference BAU scenario. Emissions continue to rise (as there is no imposed carbon cap) after an initial early dip in emissions. This characteristic corresponds to aggressive retirements for old coal and old gas plants, and their corresponding no new build constraints. As these old plants no longer generate electricity, they force the physical system to settle to a new benchmark before the system pursues its true unconstrained emissions path for the remainder of the problem horizon. Figure 5-23 presents the underlying knowledge stock trajectories per technology for the BAU constrained system, and shows the constant knowledge stock (at 1.0) for non-learning wind in this case, and the comparable rapid increase in solar and coal with CCS knowledge stocks.

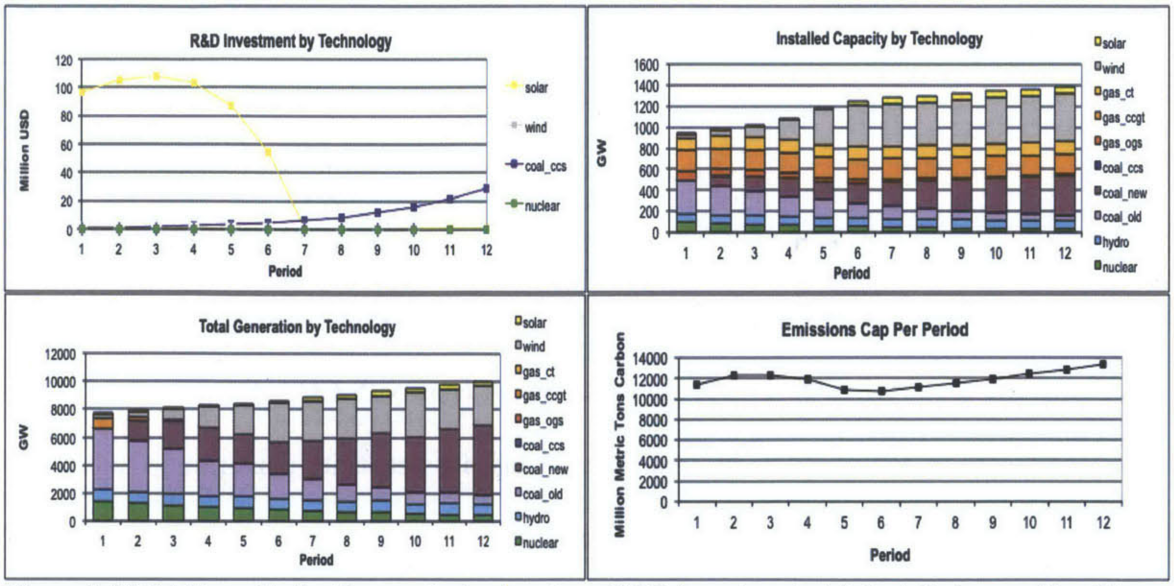


Figure 5-22 BAU results for the constrained system: R&D investments (a), installed capacities (b), total generation (c), and emissions per period (d)

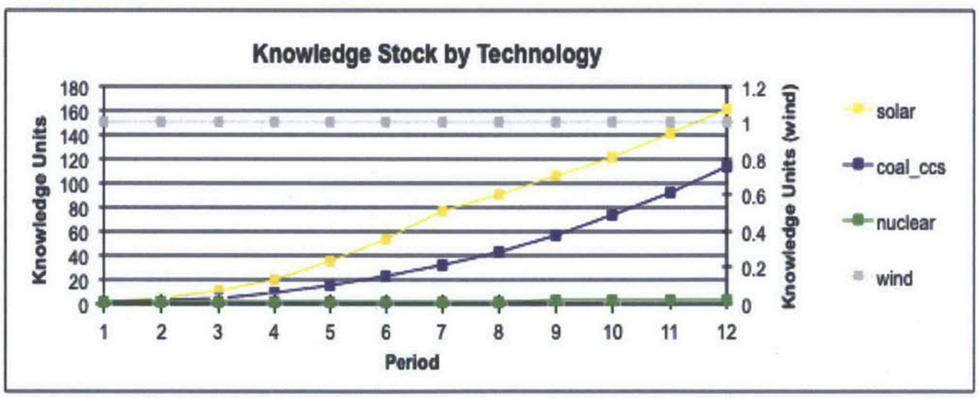


Figure 5-23 Knowledge stock trajectories under BAU in the constrained system

To study solar R&D investments and installations more closely in the context of this constrained system, the carbon target stringency level is varied, and changes in the R&D investment and capital installment patterns are compared. Weak (25% BAU) and moderate (50% BAU) carbon stringencies are imposed; results are shown in Figure 5-24 and Figure 5-25. Under carbon targets, R&D and new capacity investments for solar disappear, while those for coal with CCS increase.

On the R&D side, after a carbon target is present, coal with CCS R&D investment increases and remains constant across different targets. It also remains the only emerging technology worth investing in. The optimal investment strategy dictates the amount of coal with CCS required on the system (in both cases coal with CCS reaches its maximum capacity at ten percent of total installed capacity), and in this constrained system, the optimal (and maximum) level for R&D investment in this technology is reached quickly, under even the weakest target. The fact that coal with CCS is the only viable R&D investment is sensible here: 1) wind does not learn, so no amount of R&D investment will cause capital costs to decrease, 2) new installations of nuclear are not allowed, so although capital costs may decrease through R&D investment, the system cannot take advantage of these reductions, and 3) solar power remains severely resource constrained, diminishing its role in this carbon constrained situation.

On the capacity side, new coal with CCS capacity is added to reduce emissions and meet the caps, but only to a point as the technology has a constraint on the amount it can install in any one period. The balance of zero-emission technologies to meet the carbon targets continues to be wind, though at a more expensive installation cost than would otherwise be if it had been learning. As shown for both targets, wind continues to play a large role in the capital deployment plan. This is reasonable in this scenario, as once again: 1) coal with CCS is constrained and stops contributing to emission reductions after a certain point, and 2) solar power only generates in specific demand slices and thus needs another technology to fill in to meet the cumulative cap. As the carbon target stringency strengthens, another shift from new coal capacity additions towards new natural gas combined cycle capacity additions takes place. This is also expected as the emission rate for natural gas power plants is approximately half that of a coal plant, and under a stricter carbon target, such lower emission technologies are needed to help meet the cumulative cap.

Figure 5-25 shows the emissions time profile and total generation by technology under each of the carbon targets. The shift of focus from new coal under the weak cap towards large amounts of natural gas combined cycle is quite apparent through the approximately 1:1 displacement of new coal generation to new natural gas combined cycle generation to meet the associated caps. Once again, this change is expected given the maximum rate of change constraints for new capacity additions for the additional emerging technologies; the only slack in the system left to meet a more stringent target is natural gas.

The general solar story is perhaps most obvious in the following scenario. In terms of target stringency, there is no feasible solution for the constrained system represented in this model to reach the "strong" target studied in the original experiment in Section 5.1 above (75% BAU with (or without) and end cap). Wind and solar have constraints on how quickly they can scale up, and combined with their low resource availabilities, the system requires another technology to reliably meet demand. Combined with the fact that the scale up of coal with CCS is also constrained, and nuclear remains at dramatically low capacities (due to no new builds and retirements), natural gas combined cycle and single cycle combustion turbines are once again the only technologies available to meet demand. While emission rates for natural gas power plants are low, they are simply not low enough to meet the strict cumulative carbon target. However, it is noteworthy that when the coal with CCS scale-up constraint is lifted and the cap stringency raised slightly, coal with CCS R&D investments, installations, and operations dominate and a feasible solution is reached. The above scenarios provide a telling premise about the value of technologies like solar in this analysis under carbon cap constraints—they can remain too resource constrained to play a necessary role in meeting long-term carbon targets for a power system without effective storage.

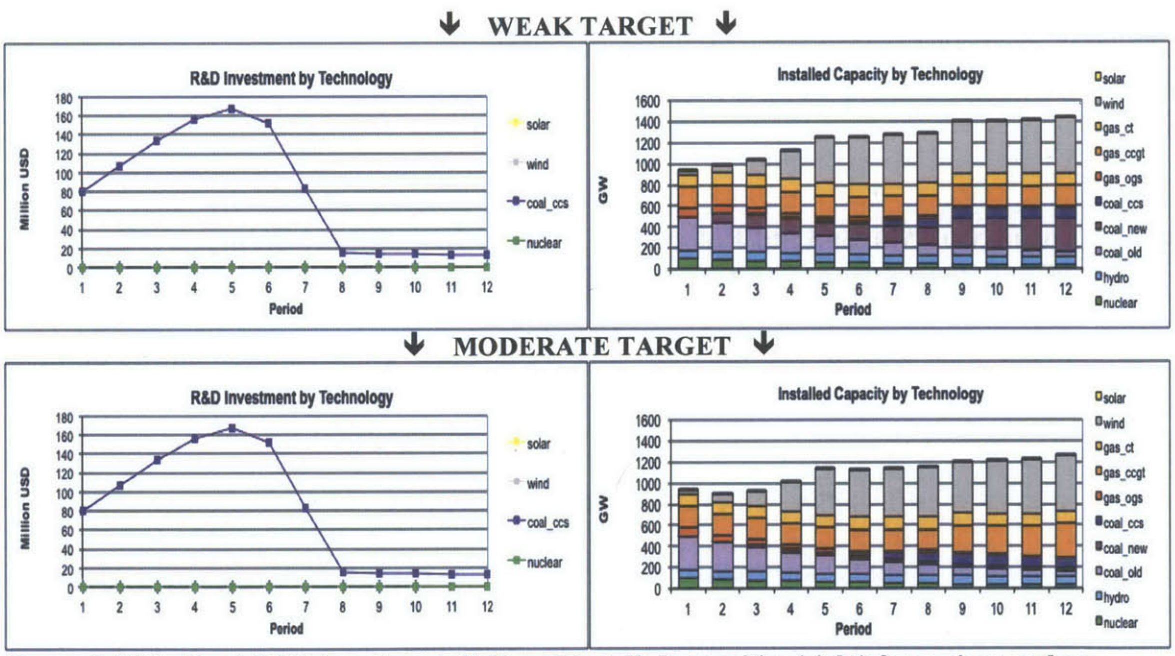


**Figure 5-24 Optimal R&D investments (left) and installed capacities (right) for various carbon reduction targets in the constrained system**

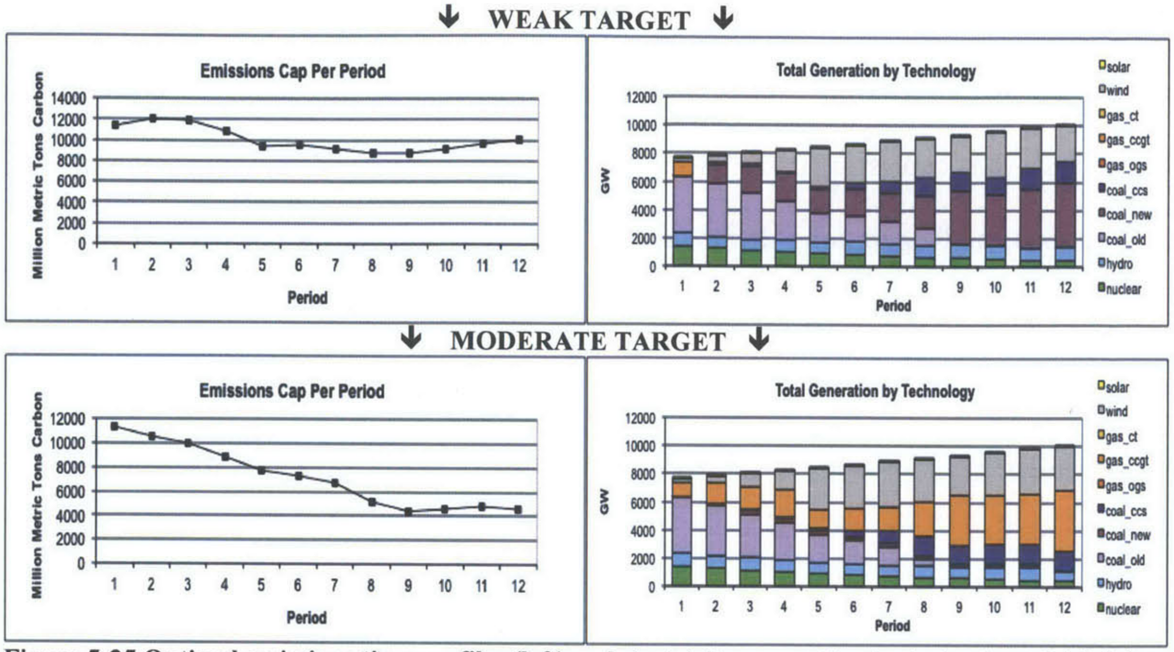


**Figure 5-25 Optimal emissions time profiles (left) and electricity generation by technology (right) for various carbon reduction targets in the constrained system**

## 5.6 Impact of Status Quo Policy on Optimal Investment Strategy: The Wind Production Tax Credit (PTC)

In the final experiment, the impact of a status quo energy policy on the optimal R&D and capital investment strategy is studied. As discussed in more detail in the system overview in Chapter 2, several types of regulatory policy instruments exist to create economic signals for industry investment in specific low-carbon generating technologies. Incentive-based instruments, or subsidies, are but one type of these mechanisms; they tend to act as price signals to guide entities' decision making in a specific direction. Such instruments include direct government expenditures or grants for specific technology adoption or action, tax credits (production-based or investment-based), low interest-loan offers or guarantees, and support for research and development of certain technologies (demonstration plants, etc.). As discussed earlier, incentives such as grants and tax credits can direct technological change through encouraging generation companies to bring new technologies to the market before manufactures are able to produce the technology in quantities large enough to be cost competitive with current technologies.

The U.S. experience with the federal production tax credit (PTC) for wind power between 1992 and 2007 provides an example of the effect that incentives can have towards technology adoption (Figure 5-26). Enacted in 1992, although with lapses in funding during specific years in between, the wind PTC is still active at present. It provides producers with 2.2¢ per kilowatt-hour for electricity generated from an eligible wind farm. The figure illustrates the growth in wind power generation capacity in the U.S. once the PTC took effect, as well as impacts of the PTC lapses in specific years.

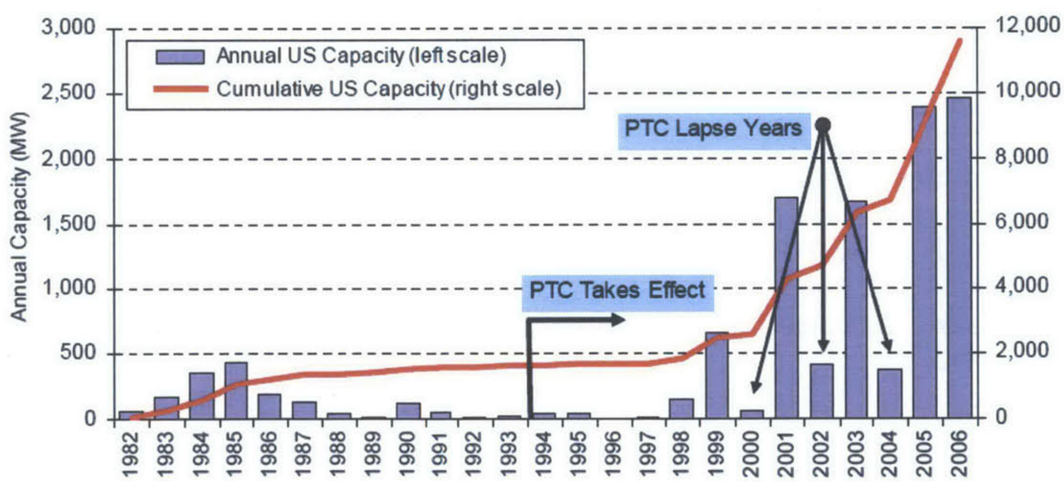


**Figure 5-26 Impact of Production Tax Credit on Wind Power Capacity Growth in the U.S.**
(Wiser, Bolinger, & Barbose, 2007)

The following experiment explores the impact of the wind PTC on the optimal investment strategy, both for R&D and new capacity decisions. While the emphasis on production tax credits for utilities is on technology deployment (i.e., new capacity additions), this experiment explores the effect such potential increases in new capacity for wind can also have on the R&D focus in the system. The reference model is used for the analysis, along with the versions of the model with carbon scenarios imposed so that impact under different carbon targets can be studied. The wind PTC is simulated in the model through decreasing the variable cost parameter for wind power. Originally, this cost is 0.519¢ per kilowatt-hour, so to test the impact of the optimal strategy under a wind PTC, the variable cost for wind becomes -1.681¢ per kilowatt-hour. Results under the wind PTC scenarios are compared to the case without a wind PTC.

Figure 5-27 present results from the wind PTC case under business-as-usual (BAU) compared with the reference results (no wind PTC) under BAU, and shows no change in either the optimal R&D investment or capital installment strategy. Furthermore, no change in investment strategy for wind or any other technology was witnessed under any of the carbon target cases; for brevity these figures have therefore been omitted. Even unrealistically high wind PTCs of ten or one hundred times the current level are not enough to cause additional building and operating of wind in these scenarios. In the problem as currently defined and numerically implemented, it is simply sub-optimal to build additional wind plants than the next most competitive (less resource constrained) technology. Overall, these results suggest that the wind PTC does not appear to be the best pathway to spur technology switching in the capital deployment plan (and thus, the R&D investment plan).

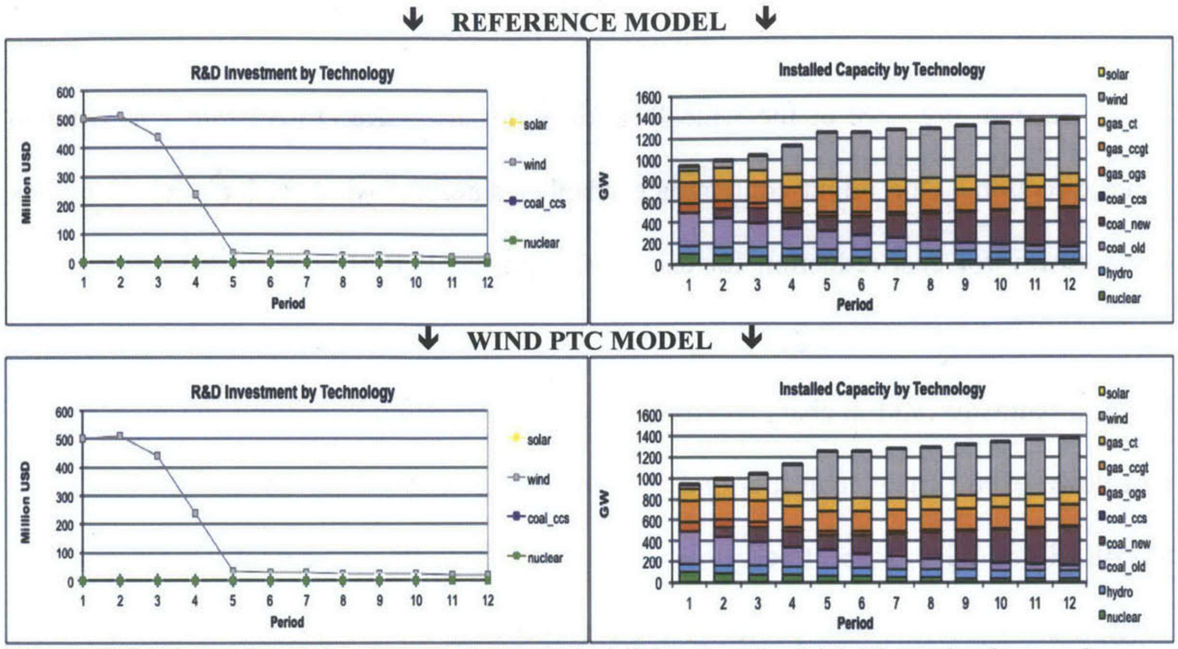


**Figure 5-27 Optimal R&D investments (left) and installed capacities (right) by technology under BAU for the Wind PTC case and the REFERENCE (No Wind PTC) case.**

Two points help explain these results. First, under the optimal plans, wind power plants are called upon to generate electricity too minimally for a production-based (per kilowatt-hour) incentive to affect the optimal technology investment strategy. Therefore, while increases in the amount of electricity generated in each demand slice and over time *are* witnessed as a result of the wind PTC, these increases are not enough to incentivize a change in the capital deployment plan (or the optimal R&D investment plan). On the other hand, direct cuts to the initial wind technology capital cost *do* noticeably change the optimal investment strategies. While the capital deployment plan still does not change, with more direct upfront capital cost reduction, optimal R&D investments decrease considerably in each period. This suggests that the model, as formulated and numerically implemented with the specific cost and technical data sets used, may be more appropriate to study the effect of direct investment-based subsidies for capital deployment, rather than indirect production-based incentives.

Second, presence of the wind PTC does not affect R&D investment in wind in either direction. One might contemplate whether since the wind PTC already provides one pathway for cost reduction for using wind power, if R&D investment to bring the capital cost of the technology down might be depressed. In this case, the role of the learning pathway (and unchanged R&D investment) is simply to bring the total system cost down even further than it is under the reference case (to $5.725 trillion NPV from $6.048 trillion NPV, respectively). While the PTC does affect the total variable cost for wind in each period (wind power plants are operating more frequently under the PTC benefit), they are still not operating enough to incentivize a deviation from the original capital deployment plan (and thus R&D investments trajectory).

Finally, although it is beyond the scope of this dissertation, it is also worth noting that the lack of R&D investment changes across the reference and wind PTC case could partially be due to the fact that the innovators in the current modeling framework are a lumped entity that includes all private equipment manufacturers, private R&D labs, and government-sponsored R&D labs, that take part in R&D for electricity generation technologies. Thus, the framework for these upstream innovators to respond to a change in downstream capacity-based behaviors is not represented adequately enough to fully assess the effects on R&D investment strategies.

Beyond the wind PTC, there are also several additional changes that are either currently occurring or can take place in the system to help wind technology deployment move forward. Strategic interconnections between grids and regions demand response programs, storage capability (although minimal), and additional flexibility through siting and supporting generation capacity can act to help the deployment (and development) of wind technology along. Testing the effect of these types of changes in the system using the new modeling framework is left for future work.

## 5.7 Summary and Key Insights

The following section provides a summary of the previous two chapters, presents highlights of results from the reference model and numerical experiments above, and draws initial conclusions about the generalizability of the results across different technologies and environmental situations.

Overall, Chapter 4 and 5 reinforce the importance of the improved decision support tool for studying combined emissions and technology policy questions applicable to the unique electricity sector. Appendix C supports the usefulness of an engineering cost-based approach that resolves the physical and operational constraints of the underlying electric power system. Operational constraints in the electricity system noticeably affect both the type and quantity of capital investment in new power plants, as well as in the amount of socially optimal R&D allocated to the different technologies across time. This is an important effect that popular economic models based on levelized costs and pre-determined operations parameters do not capture. It shows that these models may be overestimating the flexibility with which the system operates, and thus, possibly underestimating costs and overestimating actual returns on R&D. An engineering cost or hybrid modeling approach should therefore be used when investigating tangible emission reduction possibilities from the electricity sector. Section

5.3 shows the usefulness of incorporating learning-by-searching dynamics within such decision models, and suggests that models without adequate representations of both learning-by-doing and learning-by-searching may be overestimating the costs of further developing the electric power system (with or without specific environmental objectives).

The reference model and sensitivity analyses conducted provide several interesting insights about the subtle links between the innovation process, the economic processes of cost-competition between the technologies, and engineering constraints inherent in the power sector. The numerical experiments also serve as a confirmation that the new model is behaving in accordance with the physical and economic operation of the electricity system, providing reassurance that the model is suited for electricity industry analysis. Short summaries of each of the experiments are presented below, as well as the key insights gained from performing them.

*Reference Model Investment Strategy (Chapter 4.7)*

Chapter 4.7 presents results from the reference model under business-as-usual (BAU, no carbon cap). This model includes both learning-by-doing and learning-by-searching pathways with innovation parameters calibrated to the empirical literature on energy-sector technological change. Key insights:

(1) Under business as usual, the optimal investment strategy involves investing solely in wind R&D and new wind power capacity. Wind is far enough "down" both the learning-by-doing curve that a small amount of investment yields comparably large overall cost reductions, and this acts to directly bring the net present value for expanding and operating the system down.

*Optimal Investment Strategy v. Carbon Target Stringency (Section 5.1)*

This experiment studies the optimal investment strategy across various carbon target stringencies. A binding cumulative carbon cap is placed over the optimization and the goal remains to choose R&D investments and new capital investments to meet total system electricity demand at least cost. Three scenarios are studied and compared to the reference (BAU) scenario: a "weak" target defined as 25% below the BAU reference scenario, a "moderate" target at 50% below BAU, and a "strong" target at 75% below BAU *plus* a final-year target defined as achieving approximately 80% below year 2010 actual power sector emissions. The full learning-model (LBS and LBD) is used for this analysis; the only change made is in imposing the cumulative carbon caps. Key insights:

(1) Under increasing carbon target stringency, it is even more important to invest big and invest early in "base-load" electricity technologies (the power plants that are on the ground and running the majority of the time), as this is where the largest emission reductions can be gained. Under a very strict emissions target, there is a clear dominant strategy of investing in nuclear power and coal with CCS power.

(2) The optimal strategy under a carbon target (even under the strongest carbon target when nuclear and coal with CCS R&D and new capacity investments dominate) requires a portfolio approach to meeting electricity demands. Realistic maximum capacity scale-up and resource availability constraints for different technologies within the system, and their relative fixed costs (capital and other fixed) and variable costs (fuel and other variable) dictate that no one or few technologies can completely meet electricity demanded (or R&D investments).

*Optimal Investment Strategy v. Endogenous Learning Dynamics (Section 5.2)*

This experiment tests the optimal investment strategy under different learning dynamics included in (or excluded from) the numerical model. Under BAU and a moderate carbon target (50% BAU), the scenarios tested include: 1) a "no learning" scenario where no technology is permitted to learn (and reduce capital costs) via either learning-by-doing or learning-by-searching, 2) an "LBD Only" scenario where all four emerging technologies (coal with CCS, nuclear, wind, and solar) are permitted to reduce capital costs via a one-factor learning-by-doing pathway based on cumulative installed capacity, 3) an "LBS Only" scenario where all four emerging technologies are permitted to learn via a one-factor learning-by-searching pathway based on cumulative knowledge stock, and 4) an "LBD and LBS" scenario, which matches the Chapter 4 reference model scenario where all four emerging technologies are permitted to learn via a two-factor learning-by-searching and learning-by-doing pathway. All innovation parameters in each of these scenarios are kept at their corresponding reference parameters. Key insights:

(1) From least total system cost (NPV) to highest total system cost, under both BAU and the moderate target, the order of scenarios is LBD and LBS, LBD Only, LBS Only, and No Learning. In each of these scenarios, the same constraints are met and all electricity demand is met. This suggests that results from current models without representations of both learning pathways may be over-estimating costs and affirms the value of including an R&D learning pathway in energy decision models.

(2) Under a specific carbon target, new capacity decisions are dominated by the goal to meet the cumulative carbon target and are insensitive to changes in the learning

dynamics within the model. Overall, the different learning pathways (or lack of learning pathway) are insufficient to reduce capital costs by an amount necessary to induce technology switching in the capital deployment plan. In the modeling framework presented here, the learning pathways afford an opportunity to meet a specified target at a lower total system cost, but the physical system that needs to be reached and in place by the end of the planning horizon is constant under a specified cap.

(3) The behavior of R&D investment decisions tracks the capital investment requirement to meet the specified cumulative carbon cap. Also, in the presence of "free" capital cost reduction from learning-by-doing, it is optimal to invest less in R&D for a given technology. The reduction in R&D investment is based on the amount of the technology required to meet the specified carbon target, the specific parameters of the technology's learning rates, and the amount of installed capacity of the technology, which dictates how much it can take advantage of the learning-by-doing pathway.

(4) The carbon emissions time profile is also relatively insensitive to the learning-pathway included. Overall, per period emissions are driven almost exclusively by two items: the specific cumulative carbon cap target, and whether there is a learning mechanism included in the model. Following (2), the learning-pathways are not sufficient to induce technology switching in capital deployment, and each capital installment plan has one optimal generation dispatch plan associated with it to meet demand in each period. As the emissions profile is completely dictated by the generation plan, it is also insensitive to changes in the learning pathways. In each case, the optimal strategy also includes waiting to reduce emissions until the later

periods when it is necessary to meet the cumulative target. In hindsight, such a response makes sense in this type of a least-cost optimization model with discounting, but it is not initially obvious given the possibility that small investments in a high-potential, high-learning low-carbon technology category could have yielded early and drastic capital cost reductions such that it was more economical to build and operate that technology over others.

*Impact of Knowledge Stock Strength on Optimal Investment Strategy (Section 5.3)*

This experiment studies the effect of strength of knowledge stock in the innovation possibilities frontier (IPF) on the optimal R&D and capital investment strategy under the BAU and three carbon target stringencies. The reference model is used, and the parameter varied is "phi" in the IPF. The parameter is varied one at a time for each technology, holding all other technologies at their reference beta 0.54 value. Results from imposing a "low (0.1)," "medium (0.54—reference)," and "high (0.8)" value for phi are compared under a moderate (50% BAU) carbon target. A full sensitivity analysis on peak R&D investments using a range of values between 0.1 and 0.9 is also performed under all three carbon targets. Key insights:

(1) As phi increases, peak R&D investments increase monotonically, at a rate influenced by its relative need to meet the cumulative carbon target, its initial installed capacity, and its individual learning-by-doing and learning-by-searching elasticities.

(2) Changes in the R&D investment strategy for one technology do not affect decisions about R&D or capital investment for other technologies (emerging or non-emerging).

(3) Inexpensive, intermittent resource constrained technologies such as renewable wind power fills a niche in the system, and it is difficult to remove them from this niche. For these technologies, their low natural resource availabilities mean that while they are cheap and carbon-free, they are only able to contribute to a portion of meeting the cumulative carbon target. At some point, a shoulder or base-load technology such as coal, natural gas, or nuclear must physically be deployed to balance demand. In the current modeling framework (and calibrated learning parameters), this physical constraint results in a minimum amount of focus (R&D and capital investment) placed on the technology at all times in any scenario, but also on a maximum limit to how valuable R&D investment will be on minimizing total system costs.

(4) Expensive, resource constrained technologies with limited installed capacity bases (such as solar power in the stylized numerical implementation) remain locked out from playing a significant role in reducing carbon emissions in any of these scenarios, regardless of the potential strength of its learning pathways.

*Impact of R&D Program Efficiency on Optimal Investment Strategy (Section 5.4)*

This experiment studies the effect of R&D program efficiency (parameter beta in the IPF) on the optimal R&D and capital investment strategy under the BAU and the three carbon target stringencies. The reference model is once again used, and beta is varied individually for each technology. Results from imposing a "low (0.02)," "medium (0.10—reference)," and "high (0.4)" value for beta are compared under a moderate (50% BAU) carbon target. A full sensitivity analysis on peak R&D investments using a range of values between 0.02 and 0.40 is also performed under all carbon targets.

(1) The overall capital cost reductions from R&D investments can be sizable in absolute terms, but the difference in reduction potential across different R&D program efficiencies is a function of the constraints (e.g., maximum capacity scale-up rate, or resource availability) a specific technology faces in the system.

(2) Peak R&D investments increase monotonically with program efficiency, again at a rate influenced by the technology's relative need to meet the cumulative carbon target, and its installed capacity.

(3) At very high R&D program efficiencies under a strong cap, there is an additional incentive to increase the rate of R&D investment for nuclear power. The role of nuclear power in the optimal installment plan under this target, combined with its large initial capital stock, provides an opportunity to take advantage of very large cost reductions via both LBD and LBS. Such a result suggests that imposing a constant parameter value across all technologies (as is the trend in most current studies) may be keeping R&D investments artificially too low or too high relative to each other. Additionally, as the technological change literature cites uncertainty inherent in this process (R&D investment leading to technological change), and recent empirical study (Popp et al, 2012) contains evidence that the shape of the uncertainty profile may be technology specific, this experiment generally serves to motivate a need to consider technology-specific uncertainty along this dimension of the innovation process.

*The Case for Solar Technology (Section 5.5)*

Solar technology remains shut out of the optimal R&D and capital investment allocation scheme under the objective and cumulative carbon cap constraints studied throughout most of the analyses above. In this experiment, a constrained system scenario is used to study the conditions for which solar technology investments are favored. This constrained environment consists of no wind learning (neither via LBD or LBS), no new builds for nuclear power, and a maximum capacity constraint for coal with CCS technology at 10 percent of total installed capacity. All other conditions and parameters are held at reference values and the reference model is used. Key insights:

(1) Under the severely constrained system and no carbon cap, solar power R&D and capital installments enter the optimal investment strategy. However, once a carbon cap is imposed, both solar R&D and capital investment disappears and other technologies dominate the optimal investment path in order to meet more stringent targets. The reason for this solar "shut-out" remains a combination of solar power's own niche characteristic (contributing to emission reductions only to the extent that its limited resource availability allows), its initial very high capital cost, and its initial very low existing capital base. The last two characteristics make it very difficult for solar power to take advantage of either its learning-by-doing or learning-by-searching potential.

(2) Natural gas fired power, particularly highly efficient combined cycle plants, plays a large role in the constrained system as carbon stringency increases. Despite its non-learning characteristic, a combination of its relatively lower carbon emission rate (approximately half of a traditional coal plant), the maximum capacity scale-up

constraint for other technologies, and low resource availability rate for solar, creates a situation where this is the next best technology to meet demand under hard carbon targets in a constrained system. Under the hard target, generation from natural gas fired power plants meets almost 50% of system demand.

*Impact of Status Quo Energy Policy on Optimal Investment Strategy (Section 5.6)*

The purpose of the final experiment is to test the impact of real-world policies on the optimal investment strategies in emerging technologies. The policy studied is the U.S. federal wind technology production tax credit (PTC), enacted in 1992, and providing 2.2¢ per kilowatt hour of electricity produced from eligible wind farms. Under the assumption that all wind farms in the model are "eligible," the PTC is studied by decreasing the variable cost of wind power by the amount of the wind PTC. Results from including the wind PTC under BAU and all three carbon targets are compared to the reference model without the wind PTC and discussed. Key insights:

(1) In each of the scenarios studied, the wind PTC (as implemented) fails to spur technology switching in the capital installment plan, and thus in the R&D investment plan. A test where the wind PTC is artificially increased to one hundred times the current benefit shows that even at unrealistically high PTC levels, the optimal investment strategy for wind power remains insensitive. Overall, the minimal rate that wind power plants operate on the system allow the PTC to incentivize additional generation, but not additional actual deployment. A second test where the initial capital cost of wind technology is reduced (e.g., representing an installation subsidy) shows considerable decreases in the optimal R&D investment over time. This result

suggests that as formulated and numerically implemented, the current modeling framework may be more suited to subsidy-type policy analyses.

The dual purpose of Chapters 4 and 5 is to 1) introduce the structure of a new modeling framework for simultaneously studying optimal technology capital and R&D investment strategies for the electric power generation industry that considers detailed dynamics of the process of technological change, and 2) demonstrate uses and capabilities of the framework through several numerical experiments. In doing so, two generalizable technological phenomenon of the system are revealed.

First, while the technology categories in this study were depicted by names such as solar, wind, and nuclear (and based on the technology types characteristic of the existing U.S. power system), the insights drawn about their behaviors in the system and sensitivities are intended to be technology-independent. For example, the stories and trends depicted for nuclear power are typical of any zero-carbon near-fully base-loaded technology with a very high initial capital cost and good learning potential (high learning rates and a large existing capital stock). Any such technology would exhibit the effects seen here of dominance during the most stringent carbon targets.

As another example, the behaviors depicted of wind technology would be consistent with any intermittent renewable technology with natural resource constraints, favorable learning parameters, and a relatively high existing capital stock base that allowed it to take advantage of "free" learning-by-doing. Additionally, the maximum capacity scale-up constraint imposed upon wind in order to simulate realistic institutional, political, and physical constraints the system may face in quickly increasing capacities, produced results that any other similar capacity constrained technology would need to work around.

The second generalizable phenomenon seen in this study is associated with the concepts of demand-pull and technology-push, and their interaction with one another. The economics of technological change literature points to the need for both demand-pull mechanisms and technology-push mechanisms to be present for the most successful innovation (e.g., Nemet & Kammen, 2007). The two-factor learning environment in this model lends evidence to this; it is the technologies that enjoy either a relatively large existing capacity base or have the potential for long hours of operation (potential for learning-by-doing) that also enjoy allocations for R&D investment. This is most clearly seen in the case of solar power, where the technology remains shut out of R&D and capital investments due to its initial high capital cost, relatively low existing capital base, and lack of adequate operation potential. This combination allows neither learning-by-doing nor learning-by-searching reductions to be optimal (when other technologies, particularly wind which is cheaper and already more abundant, can play the role of solar power). The responses of solar power in this study are intended to be technology-independent as well, characteristic of any technology that fills a niche role in the system (given its low resource availability), prohibitively high initial capital cost, and low existing capital stock. Such technologies may need to be transplanted into a different system in order to flourish without additional support.

**Table 5-1 Model Assumptions and Parameter Definitions for Numerical Experiments**

| Section No. | Section Name | Corresponding Parameter and Reference Value | Experiment Parameter Value(s) | Notes |
|---|---|---|---|---|
| **Section 5.1** | Optimal Investment v. Carbon Target Stringency | *ecap* = 260,000 | 75% BAU (Weak Target): 195,000<br>50% BAU (Mod Target): 130,000<br>25% BAU (Strong Target): 65,000 + End Cap* | All values are in Million Metric Tons<br>* Requires per period emissions after Period 12 to be $\leq$ ~ 80% below 2010 emissions (2500 Million Metric Tons) |
| **Section 5.2** | Optimal Investment v. Endogenous Learning Dynamics | $\eta 1_g$, $\eta 2_g$ (Reference LBD and LBS Elasticities from Table 4-2 See Notes) | No Learning: $\eta 1$, $\eta 2$ = 0.00<br>LBD Only: $\eta 1$ = Ref.; $\eta 2$ = 0.00<br>LBS Only: $\eta 1$ = 0.00; $\eta 2$ = Ref.<br>LBD and LBS: $\eta 1$, $\eta 2$ = Ref. | Reference / Table 4-2 Values:<br>Coal w/ CCS: $\eta 1$ = 0.05889; $\eta 2$ = 0.02915<br>Nuclear: $\eta 1$ = 0.05889; $\eta 2$ = 0.02915<br>Wind: $\eta 1$ = 0.25154; $\eta 2$ = 0.10470<br>Solar: $\eta 1$ = 0.41504; $\eta 2$ = 0.15200 |
| **Section 5.3** | Optimal Investment v. Knowledge Stock Strength | $\Phi$ = 0.54* | $\Phi$ = [0.1,0.9] ** | * For all emerging technologies (coal_ccs, nuclear, wind, and solar)<br>** One technology varied at a time, holding other $\Phi$s at reference value |
| **Section 5.4** | Optimal Investment v. R&D Program Efficiency | $\beta$ = 0.10* | $\beta$ = [0.02, 0.18]** &<br>$\beta$ = 0.40** | * For all emerging technologies (coal_ccs, nuclear, wind, and solar)<br>** One technology varied at a time, holding other $\beta$s at reference value |
| **Section 5.5** | The Case for Solar Technology | $\eta 1_{wind}$ = 0.25154, $\eta 2_{wind}$ = 0.10470<br>$NEW\_CAPACITY_{t,nuclear} \neq 0$ | $\eta 1_{wind}$, $\eta 2_{wind}$ = 0<br>$max\_capacity_{coal\_ccs}$ = 0.10<br>$NEW\_CAPACITY_{t,nuclear}$ = 0 | |
| **Section 5.6** | Optimal Investment under a Wind PTC | $var\_om\_rate_{wind}$ = 0.00519 | $var\_om\_rate_{wind}$ = -0.01681 | All values are in million $ per GWh<br>* Wind PTC is 2.2¢ per kWh |

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# Chapter 6 Investment Planning under Endogenous Technological Change Uncertainty: Description of the Stochastic Modeling Framework

This chapter presents the structure and solution approach for the reference electricity R&D and generation capital investment problem under endogenous technological change uncertainty. A key motivating research question of this dissertation is how the optimal investment strategy in a deterministic setting changes when uncertainty and learning are explicitly considered in a formal stochastic setting. The problem is thus now formulated as a formal sequential decision under uncertainty problem, where the decision maker has the opportunity to learn about the uncertainty and revise his decisions over time. The solution to the problem is a flexible investment strategy, which adapts to technological change outcomes from R&D.

The first section presents the formulation of the sequential decision under uncertainty problem, highlighting the common elements from the deterministic analyses in Chapters 4 and 5. The second section explains the method for characterizing and representing the technological change uncertainty, applied within the stochastic modeling framework, and describes the empirical motivation for doing so. The final section presents an approximate dynamic programming implementation developed and utilized for solving the new stochastic problem. The methods used for sampling and approximating a cost function for a high-dimensional solution space are emphasized.

## 6.1 Formulation of the Sequential Decision under Uncertainty Problem

Chapters 4 and 5 present a model that solves for the optimal electricity technology R&D and capital investment plan to reliably meet electricity demand under a range of different carbon emissions targets, assuming perfect information. Learning-by-searching (LBS) technological change is endogenous in the numerical model used for the analysis, allowing R&D investments to lower the capital cost of installing new generation capital over time. The question therefore is one of inter-temporally balancing 1) the near-term cost of investment in R&D and the long-term benefit of lowered future capital costs, with 2) the cost of installing power plants at their current costs and the benefit of the early emissions reductions they might afford. Because multiple technology groups have the opportunity to be improved through the LBS pathway and be installed to generate electricity, there is also a question of intra-temporal balancing between investing among different technologies (e.g., R&D portfolio and capital investment portfolio optimization).

In the previous problem, however, the amount of technological change (e.g., capital cost reduction) that results from a given level of R&D investment is known with perfect foresight. The inquiry made through this and the following chapter removes this limiting assumption, allowing for direct investigation of the optimal inter-temporal and intra-temporal investment strategy under endogenous technological change uncertainty.

### *6.1.1 Overall Framework*

The nature and structure of the underlying problem is maintained from that of the deterministic study design of Chapters 4 and 5, but with adjustments to highlight the effect of uncertainty and learning on the optimal strategy. The planning horizon for the model remains at 60-years, but time steps are now 10 years long to allow for six distinct decision periods. All time-indexed exogenous parameters and endogenous variable representations used in the original 5-year step model previously are adjusted to account for these longer time steps. The analysis here is repeated under different cumulative carbon target scenarios—a business-as-usual (BAU) scenario with no carbon cap and a 50% below BAU scenario with a carbon cap—in order to understand how different possible carbon target stringencies affect the optimal investment path under uncertainty.

The stochastic version also loosely approximates the structure of the U.S. electric power generation system with respect to total installed capacity, electricity demand, and electricity demand growth. However, the number of generation technology groups is reduced to five in order to represent more generic power plant technology types: conventional coal, coal with carbon capture and sequestration (CCS), natural gas combined cycle, natural gas combustion turbines, and wind. The main goal of the stochastic investigation is to develop the numerical modeling framework for decision support under uncertainty, and to understand if and how the investment strategy under uncertainty differs from a deterministically designed strategy. This insight can be gained from focusing on a small number of technologies that span a spectrum of key technology characteristics. These five technology groups have been chosen because they represent baseload (conventional coal and coal with CCS), "shoulder" load (natural gas combined cycle), "peak" load (natural gas combustion turbine), and intermittent renewable (wind) technologies. Therefore, although the cost structures for these technology groups have been adopted from the respective technologies used in the original 10-technology model, for the purposes of illustration these technologies can be thought of as representing a general class of technology. Table 6-1 presents the generation cost data associated with these technology groups, as used in the stochastic study. The structure and parameters used for the technological change module and the representation of electricity system operations are also identical to that of the original model.

Finally, a non-linear programming (deterministic) formulation of this 5-technology model, using an identical solution approach as that described in Chapter 4 for the full 12-period, 10-technology model, exhibits a similar behavior as the full deterministic model with respect to R&D investment strategy and generating capacity additions under the different cumulative carbon targets (see Appendix D Part 1). This provides confidence in use of the reduced-form model for the current analysis.

**Table 6-1 Generator Cost Data for 5-Technology Model**

| Technology | Initial Capacity [GW] | 10-year Retirement Rates [%] | Heat Rate [MMbtu/MWh] | Initial Capital Cost [$/kW-knowledgeunit] | Fixed O&M Cost [$/kW-year] | Initial Fuel Cost [$/MMBtu] | Other Variable Cost [$/MWh] | Emissions Rate [lbs/MMbtu] | Annual Availability Rate [%] |
|---|---|---|---|---|---|---|---|---|---|
| Conventional Coal | 494.816 | 22.5 | 8.80 | 3167 | 35.970 | 2.07 | 4.25 | 204.12 | 85 |
| Coal with CCS | 1.00 | - | 12.00 | 5099 | 76.620 | 2.07 | 9.05 | 20.41 | 85 |
| Gas Combustion Turbine | 280.890 | 36.0 | 6.43 | 1003 | 14.620 | 9.10 | 3.11 | 121.83 | 85 |
| Gas Combined Cycle | 120.382 | - | 9.70 | 665 | 6.700 | 9.10 | 9.87 | 121.83 | 90 |
| Wind | 35.296 | - | - | 2438 | 28.070 | - | 5.19 | - | 30 |

Sources: (Adapted from) National Renewable Energy Laboratory, 2009; EIA, 2011b.

### *6.1.2 Decisions and Uncertainties*

Of the five technology groups represented in the model, coal with CCS and wind technologies represent "emerging" technologies and have the ability to learn through both learning-by-searching (LBS) and learning-by-doing (LBD) to endogenously decrease their capital costs. Uncertainty is introduced through the LBS pathway for these technologies, to represent alternative plausible outcomes of investing in R&D programs. The uncertainty is incorporated as representing differing returns on R&D investment. Figure 6-1 shows a conceptual diagram for the introduction of uncertainty in the new model. Full details about the characterization and specific point of entry in the numerical framework are provided in Section 6.2 below.

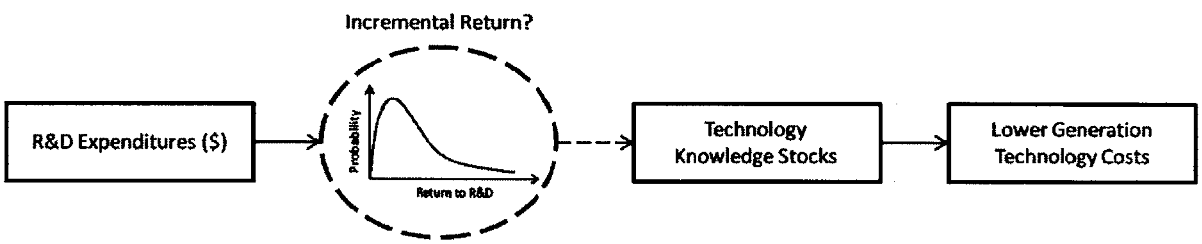


**Figure 6-1 Conceptual diagram of the relationship between R&D investment and technological change** (A single period is represented)

The variables to be optimized in the stochastic model include R&D investments for the two emerging technology groups—coal with CCS and wind—in each of the six decision periods. Capital investment decisions are fixed for the stochastic analysis based on the results of the deterministic model. For a given cumulative carbon target, capital investment is insensitive to changes in R&D outcome. As explained in detail in Chapter 5, this is due to the fact that the LBS pathway included in the numerical model does not reduce capital costs sufficiently to change the relative preference ordering for investment within a given carbon scenario. Therefore, given the objective of the stochastic analysis to understand the effect of technological change uncertainty (i.e., R&D outcome uncertainty) on the optimal investment strategy, capital investment decisions for all five technologies are fixed at their optimal deterministic paths for a given carbon target. [11]

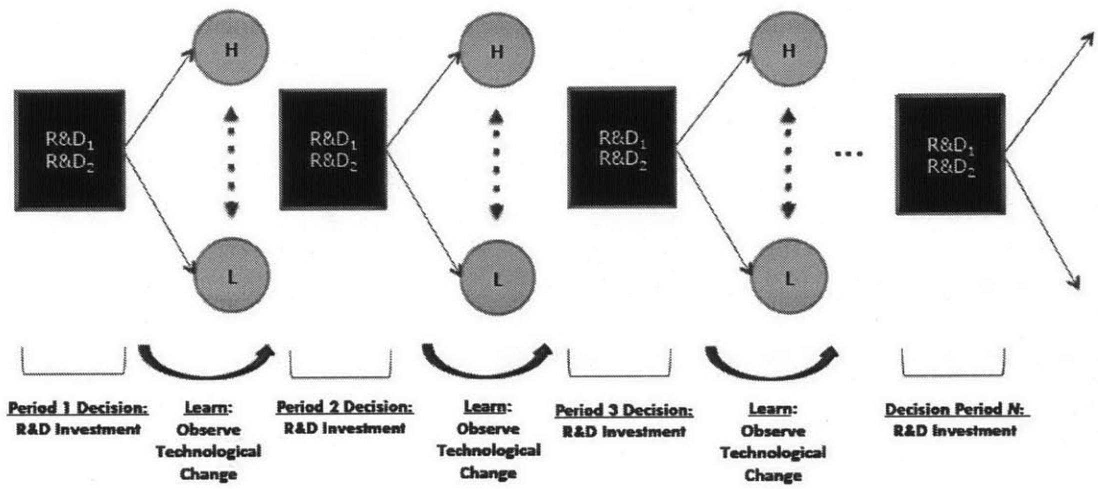


**Figure 6-2 Schematic of sequential R&D investment decisions under technological change uncertainty**

Figure 6-2 provides a schematic of the multi-period sequential decision under uncertainty problem. R&D investment decisions are made for each of the two technology groups in each decision period, *prior* to learning about the amount of technological change those R&D investment decisions will contribute to. R&D decisions are

[11] Note that the trajectory for capital investments in the stochastic model is being fixed because it is the *same* as the optimal deterministic trajectory. However, this does result in the only open decision variables being the optimal (stochastic) trajectory of R&D investments in coal with CCS and wind technologies, in order to minimize costs via LBS.

represented as a continuous range of investment values in the problem, although they are operationally (finely) discretized for the numerical implementation. After each decision stage, the decision maker learns about the realized technological change for each technology group, and has an opportunity to revise his next decision based on the technology "state of the world" he finds himself in. Alternate plausible outcomes are represented as continuous probability distributions in the numerical implementation.

### *6.1.3 Mathematical Formulation*

Formally, the stochastic program is shown in Equation 6.1.1, where $REBACK_{g,t}$ is the R&D investment level into technology group $g$ in decision stage $t$, $\theta_{g,t}$ is the uncertain technological change for technology group $g$ in stage $t$, and $C_t$ is the discounted total system cost in stage $t$ computed by the underlying electricity R&D and capital investment planning model equations.

$$\min_{REBACK_{g,1}} \left\{ C_1 + \min_{REBACK_{g,2}} E_{\theta_{g,t}}[C_2 + \cdots] \right\} \qquad \text{(Eq. 6.1.1)}$$

The framework of stochastic dynamic programming is employed to numerically solve the sequential decision under uncertainty problem. The approach uses the Bellman equation (Bellman, 2003) to decompose the multi-period problem into a simpler set of conditions that must hold for all decision periods, $t$:

$$V_t = \min_{REBACK_{g,t}} \{C_t + E[V_{t+1}(REBACK_{g,t}, \theta_{g,t})]\} \qquad \text{(Eq. 6.1.2)}$$

Using Equation 6.1.2, each decision period is then solved separately for the optimal investment strategy, conditional on the state of the world. As Equation 6.1.2 shows, it does so by balancing the near-term (current) total system costs with expected future system costs. Figure 6-3 schematically depicts this optimization of the Bellman Value function that occurs in each decision period. Current costs increase over current period R&D investments, as the R&D effort must be paid for in the current time periods. Expected future costs decrease as a function of current period R&D investments, as the capital costs of the technologies decrease over time and R&D investments. Finally, when combined, these cost trajectories result in a function over current period R&D investments that can be optimized.

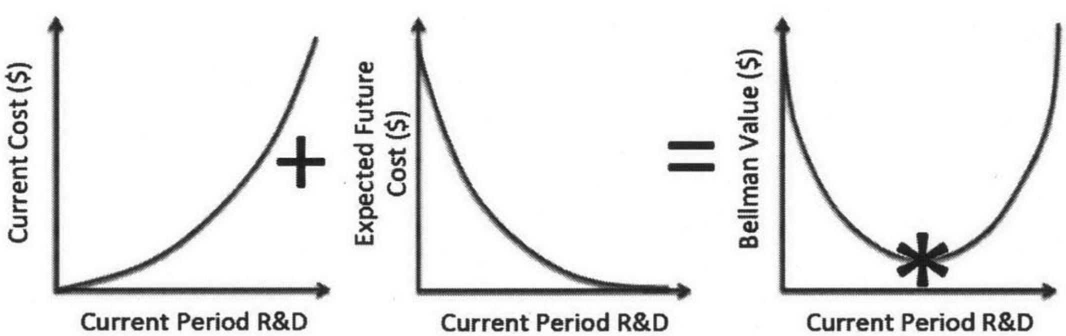


**Figure 6-3 Schematic of the stochastic dynamic programming optimization method of balancing near-term costs and expected future costs**

Figure 6-4 and Figure 6-5 below show the actual current stage costs and expected future costs as a function of each of the possible R&D investment decisions in the first stage, holding the investment decision for the other technology constant at its optimal stochastic decision. The costs shown are from a BAU scenario. Note that Figure 6-3 is meant only to schematically depict the balancing of current stage and expected next state costs; functional forms of actual decision problems vary widely. In this electricity technology investment planning problem, the current cost linearly increases in R&D investments, and the expected future costs exponentially decrease in R&D investments.

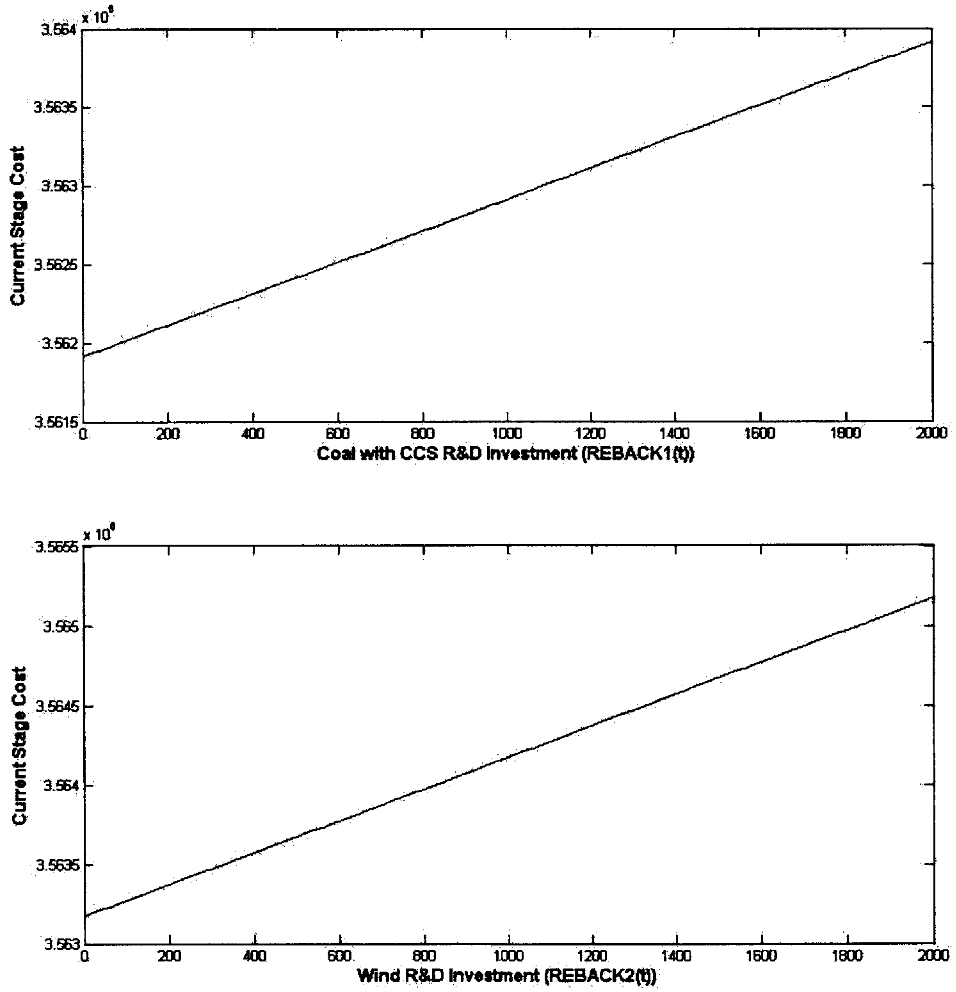


**Figure 6-4 Current stage costs as a function of coal with CCS (top) and wind (bottom) R&D investment in first decision period when R&D investment efficiency is uncertain[12]**

12 Current stage costs are a function of single technology R&D decisions (while holding the other technology R&D constant).

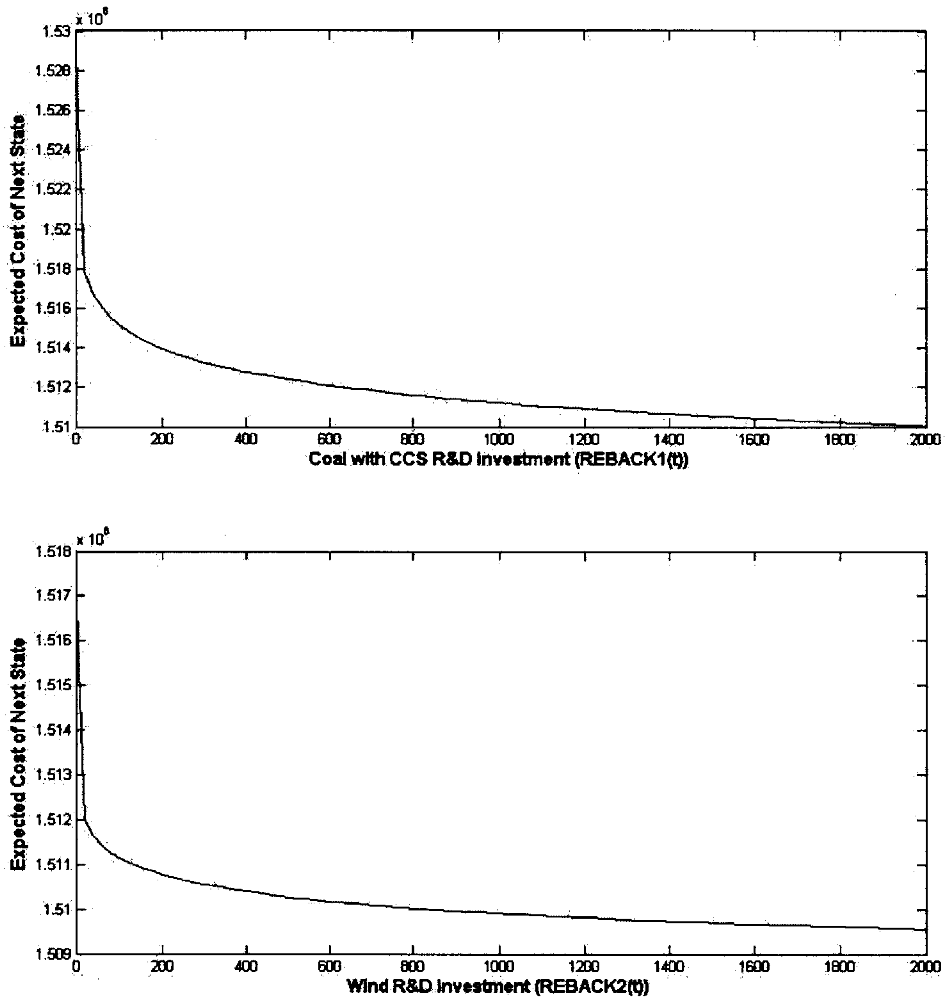


**Figure 6-5 Expected future costs as a function of coal with CCS (top) and Wind (bottom) R&D investment in first decision stage when R&D investment efficiency is uncertain** [13]

[13] Ibid.

## 6.2 Characterization of Technological Change Uncertainty

### *6.2.1 Representation in the Numerical Model*

Technological change uncertainty is represented in the sequential decision model as a multiplicative shock to the parameter representing the efficiency of R&D within the innovation possibilities frontier (IPF). For reference, the IPF and related equations of the dynamic technological change module from the deterministic model are shown again below in Equations 6.2.3-6.2.5. The structure of the module is identical in the stochastic framework. Shown in Equation 6.2.3, the uncertainty ($\theta$) is placed around the parameter β, which ultimately results in different realizations for cost reduction of $CAPC_{t,g}$, the capital cost in time period $t$ for technology $g$, through incremental returns on the R&D investment (*NEWHEB*), and subsequent endogenous growth of the cumulative knowledge stock (*HEBACK*).

$$NEWHEB_{t,g} = \alpha_g REBACK_{t,g}^{\beta_g(\theta_{t,g})} HEBACK_{t,g}^{\phi_t} \qquad \text{(Eq. 6.2.3)}$$

$$CAPC_{t,g} = \frac{CAPC_{0,g}}{(CAPACITY_{t,g}^{\eta 1_g})(HEBACK_{t,g}^{\eta 2_g})} \qquad \text{(Eq. 6.2.4)}$$

$$HEBACK_{t+1,g} = NEWHEB_{t,g} + \delta_g HEBACK_{t,g} \qquad \text{(Eq. 6.2.5)}$$

### *6.2.2 Characterization*

Probability density functions are used to capture the uncertain nature of the innovation process and R&D (Mansfield, 1968; Evenson & Kislev, 1975). In the reference stochastic model, the multiplicative shock to the R&D efficiency parameter is characterized by a Lognormal probability density function (PDF), with location parameter, $\mu = 0$, and scale parameter, $\sigma = 0.5$ (Figure 6-6). The mean of the shock is adjusted to 1.0 to ensure that the mean of the stochastic version is identical to the deterministic model.

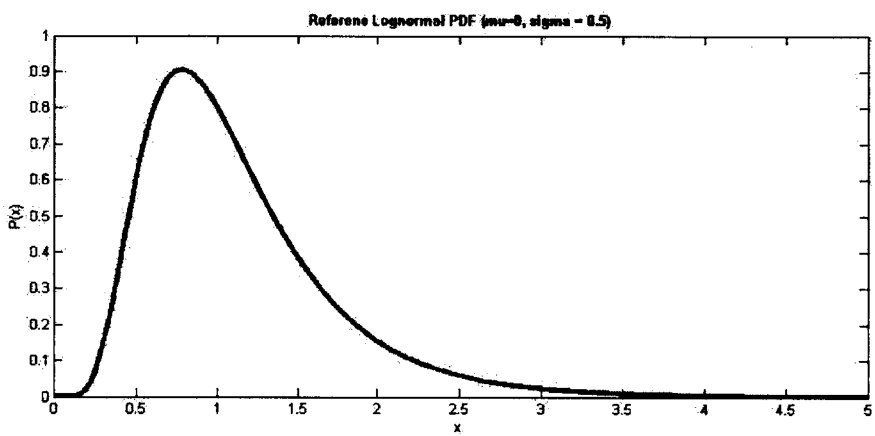


**Figure 6-6 A reference Lognormal probability distribution ($\mu$=0; $\sigma$= 0.5) is used to represent a "shock" to R&D investment efficiency and inherent stochasticity and skewness in R&D outcomes**[14]

A Lognormal distribution is used as the reference PDF because empirical evidence shows that the probability distributions for describing outcomes of innovation processes are also highly skewed, with the majority of returns to R&D being small

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[14] To ensure that the deterministic model mean is preserved, samples from the Lognormal distributions used in the stochastic model are mean-adjusted; the PDFs shown above is the original PDF.

incremental improvements to the existing knowledge stock and far fewer opportunities for high-value "breakthrough" returns (Jaffe & Trajtenberg, 2002; Pakes, 1986; Scherer & Harhoff, 2000).

Figure 6-7 shows examples of such skewed distributions for returns to electricity technology-related R&D (Popp et al., 2012). There are several alternative empirical indicators for returns to innovative effort. Patents counts, along with the numbers of forward citations they receive by other patents, are commonly used to simultaneously represent the quantity and quality of the R&D return (Jaffe & Trajtenberg, 2002; Griliches, 1990; Popp, 2002; Popp et al., 2012). The figures present the distribution of forward citations received by patents from a given filing year granted by the U.S. Patent and Trade Office (USPTO) from other patents within the same technology field. They show that many patents are never cited and that a long upper tail exists with a small number of highly cited patents. Popp et al. (2012) notes that the general skewed nature of these distributions hold across different technologies and throughout time.

Moreover, while each of the profiles for R&D returns is skewed, they also retain characteristic shapes. Some technology groups display a "high risk-high reward" profile type, which corresponds to frequent opportunities for very small returns and rare opportunity for very large returns—a characteristic "exponential" shape. Other technology groups display a return profile more akin to "slow and steady progress" in the innovation process, corresponding to more frequent moderate returns. These characteristic profile shapes also appear to endure over a wide range of patent filing years.

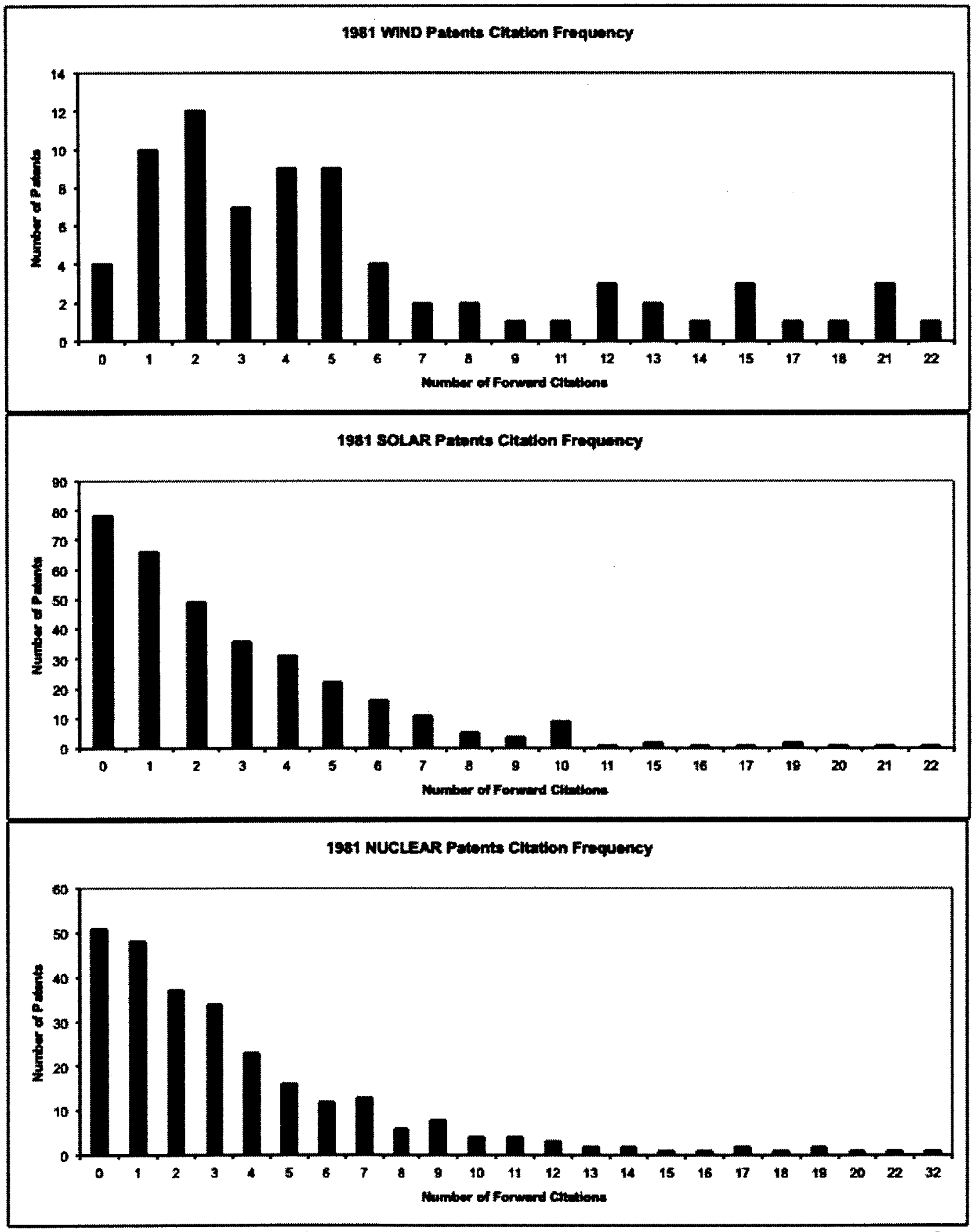


**Figure 6-7 Forward citation frequency distributions for wind (top), solar (middle), and nuclear (bottom) energy U.S. patents (Popp et al., 2012) [15]**

[15] The horizontal axis shows the number of forward citations received; the vertical axis shows the number of patents receiving that many citations.

Assigning specific distribution types and parameters to specific technology groups within the reduced 5-technology model is beyond the scope of the dissertation. However, qualitatively motivated by the existence of these different profiles, alternate PDFs are used in the analyses that follow in Chapters 7 to highlight the overall effect of skewness and uncertainty on the optimal investment strategy. For example, to study the effect of skewness explicitly, the distribution for the shocks are applied as an Exponential PDF ($\lambda = 1.0$) and compared to a symmetric Normal PDF ($\mu = 1.0$, $\sigma = 1.0$). (Figure 6-8).

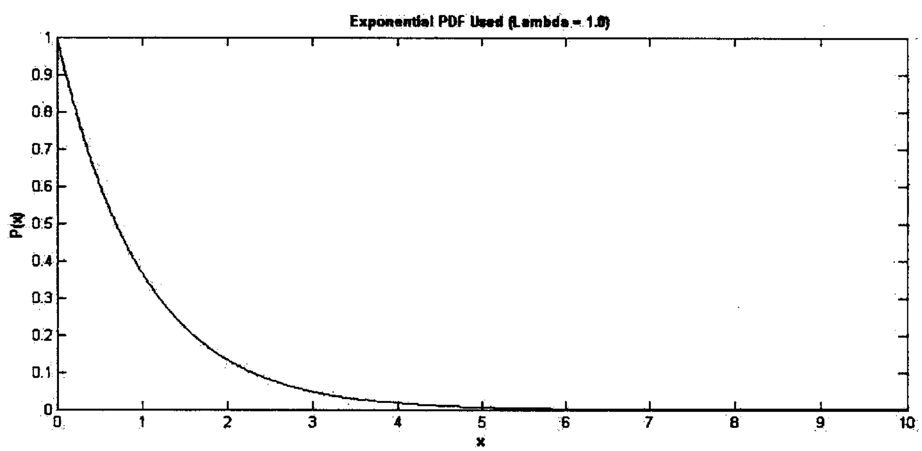


**Figure 6-8 An Exponential probability distribution ($\lambda$= 1.0) is used to represent a "shock" to R&D investment efficiency and the general skewed nature of R&D outcomes.**

The shocks are sampled as i.i.d. (e.g., uncorrelated over time) based on previous studies of technological change that indicate there is no evidence of correlation over time in the shocks or noise around the mean trend (Popp et al., 2009; Parpas & Webster, 2012). Finally, in order to retain the decreasing returns to scale Cobb-Douglas form of the reference IPF (i.e., the sum of elasticities less than 1) and diminishing returns to research (beta between 0 and 1), the shocks are constrained to values between 0.2 and 4.0 such that the final parameter value for R&D efficiency is between 0.02 and 0.40. This mimics the approach taken in the deterministic study and sensitivity analyses.

## 6.3 Approximate Dynamic Programming Implementation

The stochastic dynamic programming (SDP) problem formulated above is a finite horizon problem, and traditionally solved as a Markov Decision Problem (Bertsekas, 2007) using a backward induction algorithm. The algorithm exhaustively iterates over the state, decision, and uncertainty spaces for each decision period to calculate the exact Bellman Value function and corresponding "policy" (decision strategy) function in each period. Because the decision and state spaces are all continuous, this approach requires discretization for each variable. For the full stochastic problem formulated above, there are at least two state variables that must be known at each stage in order to make the next decision: the knowledge stocks for the emerging technology groups ($HEBACK_1(t)$ and $HEBACK_2(t)$). In the problem formulated above, new generating capacity decisions are fixed; otherwise, this would add another six state variables to the list as installed capacities for each of the five technology groups plus the total cumulative carbon dioxide emissions level. All of these variables require knowledge of their own value, or another endogenous variable's previous value to calculate the next value (See Chapter 4 or Appendix A).

In addition to the state variables, conventional dynamic programming also iterates over discretized values of the decisions, wind energy R&D investment ($REBACK_1(t)$) and coal with CCS R&D investment ($REBACK_2(t)$), and the corresponding R&D efficiency shocks for coal with CCS and wind ($\theta_1(t)$ and $\theta_2(t)$, respectively). This results in at least a 6-dimensional problem in each of the six decision periods, which is already a very large problem even if the discrete intervals are at an unsatisfyingly coarse resolution.

Instead of traditional backward induction, a new approximate dynamic programming (ADP) algorithm is used for efficiently solving this problem, shown in Algorithm 1 (Webster, Santen, & Parpas, 2012) and explained in detail below. ADP is a family of methods (e.g., Bertsekas & Tsitsiklis 1996; Powell 2007) that approximates the value function in each period by adaptively sampling the state space to focus on lower expected value states until the Bellman Value function converges. Thus, the dimensionality of the original problem is dramatically reduced. Figure 6-9 conceptually illustrates this dimensionality reduction between conventional stochastic dynamic programming and approximate dynamic programming for a hypothetical five-period decision under uncertainty problem. Two critical design choices in any efficient ADP algorithm are: 1) the sampling strategy, and 2) the value function approximation, described next.

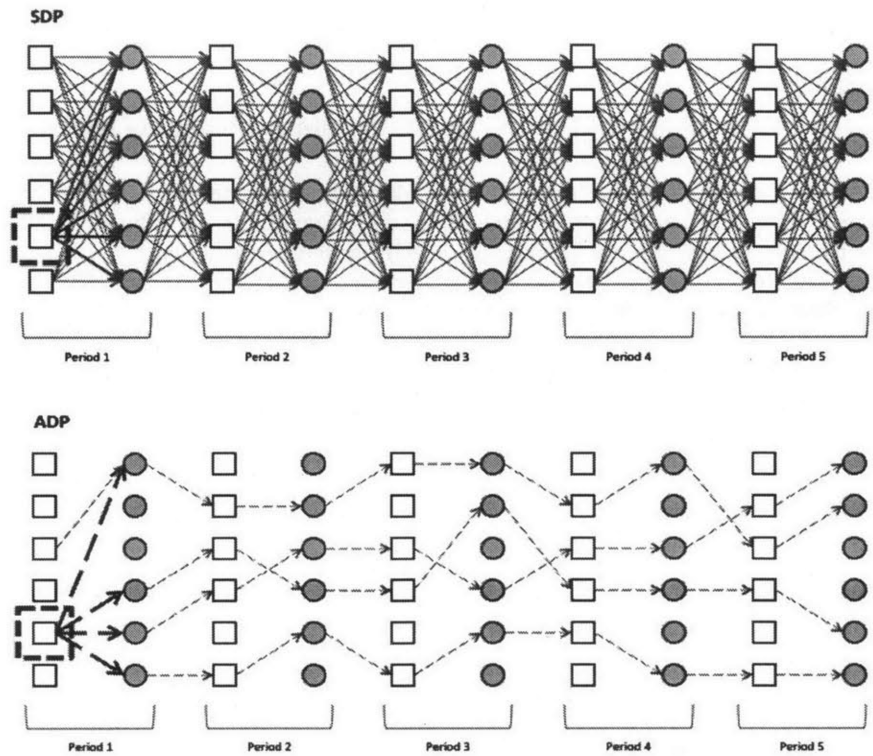


**Figure 6-9 Conceptual comparison of SDP and ADP search space. Decisions are represented by boxes, uncertainties by circles, and the optimal first-period decision vector is bolded**

**Algorithm 1:**
**Electricity Technology R&D and Capital Investment Planning ADP**

**Input:** Decision periods, $N$, bootstrap iterations, $bs$, possible decisions, *REBACK1* and *REBACK2*, uncertainty variables, $\theta 1$ and $\theta 2 \sim LN(0,\sigma)$, system state $s_0 \in S$ at time $t_0$, system state transition equations $F(REBACK1, REBACK2, \theta 1, \theta 2)$, convergence criterion, $\bar{\epsilon}$.

__Phase I Initialization-Bootstrap__: While iteration $i \leq bs$,

**1. Forward Pass**

**Loop** over $t$ from 1 to $N$, Latin Hypercube Sampling from $\theta 1$ and $\theta 2$, and *REBACK1* and *REBACK2*, and set current cost as:

$$C_t(s_i) = C(FC_t + VC_t + REBACK1_t + REBACK2_t)(1 + \rho)^{-t},$$

where $s_i$ is the current system state, $FC_t$ and $VC_t$ are simulated current total fixed and variable costs from the electricity generation problem, and $\rho$ is a discount rate.

**2. Backward Pass**

**Loop** over $t$ from $N$ to 1, setting the Bellman Value as:

$$v_t(s_i) = \left(C_t(s_i) + v_{t+1}(y_i | s_i)\right),$$

where $y_i$ is the sampled next system state resulting from $REBACK1_t$ and $REBACK2_t$ and $\theta 1_t$ and $\theta 2_t$ and $v_N$ is a pre-defined terminal value.

**3. Construct First Estimate of Value Function:** When $i = bs$, use MLS to set:

$$\hat{v}_t(s) = \Phi(s) r_o(s),$$

where $\Phi$ is a row vector of basis functions that depend on the state, $s$, and $r_0$ is a column vector of coefficients that solves:

$$\min_{r_0} \sum_{s_i} \left(\hat{v}_t(s_i) - \Phi(s_i) r_0(s_i)\right)^2,$$

for all sampled states $s_i$.

__Phase II Main Loop-Optimization__: While iteration $i > bs$,

**1. Forward Pass**

**Loop** over $t$ from 1 to $N$, sampling $\theta 1$ and $\theta 2$ randomly and choosing decisions *REBACK1* and *REBACK2* that achieve:

$$\min_{REBACK1, REBACK2} [C_t(s_i) + E\{v_{t+1}(y_i | s_i)\}],$$

where

$$E\{v_{t+1}(y_i | s_i)\} = \widehat{v_{t+1}}\left(REBACK1_t, REBACK2_t, \theta 1_t \theta 2_t\right).$$

Set current cost, $C_t(s_i)$, as in Phase I.

**- Continued on next page -**

**Algorithm 1 (continued)**

**2. Backward Pass**
**Loop** over $t$ from $N$ to 1, setting the new Bellman Value as:

$$v_t(s_i) = \left(R_t\,(s_i) + \widehat{\overline{v_{t+1}}}\,(y_i|s_i)\right),$$

where $y_i$ is the sampled next system state.

**Update** $r_i\,(s_i)$
if $s_i \in S$, set:

$$v_t(s_i) = C_t(s_i) + \widehat{\overline{v_{t+1}}}(y_i|s_i),$$

else if $s_i \notin S$, **add** $v_t(s_i)$ to the existing set of saved samples.

**Exit** when:

$$\bar{\epsilon} > \left|\overline{v_{1,t}} - \overline{v_{1,t-1}},\right|$$

where $\bar{\epsilon}$ represents the change in the moving average of the total Bellman Value in the initial stage.

**Output:** Optimal first-period decisions, $REBACK1_1^*$ and $REBACK2_1^*$, value function approximations, $v_t^*(s)$.

### *6.3.1 Sampling Strategy*

The solution algorithm consists of two phases. In Phase I, the bootstrap phase, a Latin Hypercube Sampling approach (McKay, Beckman, & Conover, 1979) is used to explore both the decision space over all periods and the uncertainty space. These sample paths are simulated forward, and the resulting Bellman Values for the sample states and decisions are saved for each decision period. The full set of bootstrap sample Bellman Values are then used to produce the first estimate of the value function approximation for each decision period, using the method described below. One critical advantage of forward sampling is that it enables a reduction in the number of states needed to approximate the value function.

In Phase II, the shock to R&D efficiency in each period is randomly sampled to obtain a sample path, and optimal decisions in each period are chosen using the current value function approximations for the value of the next state, and simulated R&D and generation capacity investment planning equations for the current costs. The overall sampling approach is an efficient (stratified) pure "explore" strategy in Phase I and a pure "exploit" strategy in Phase II. Figure 6-10 illustrates the algorithm sampling through these phases for a single run. The algorithm's pure explore strategy during Phase I is clearly shown through iterations 1 to 1000, where the entire decision space is searched to gather information about the Bellman Value function. Phase II is also clearly seen from iteration 1001 to 2000, where the pure exploit strategy takes over and the algorithm focuses on promising (i.e., low expected value) states until eventually converging on the final decision.

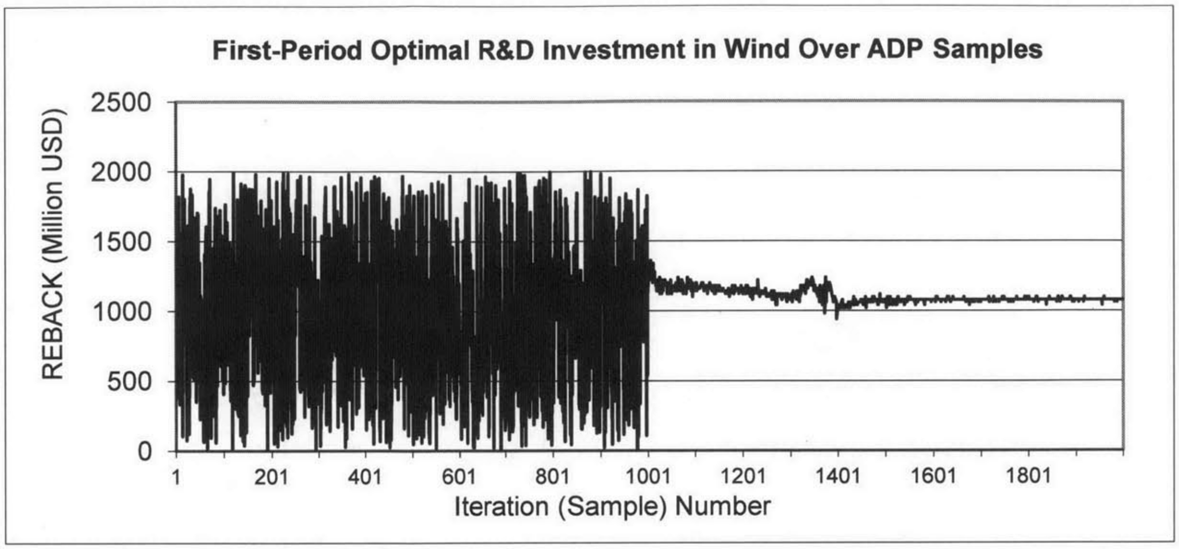


**Figure 6-10 Optimal first-period R&D investment decision for wind energy technology over ADP samples** (Two sampling phases are seen, pure explore (iteration 1-1000) and pure exploit (iteration 1001-2000))

### *6.3.2 Bellman Value Function Approximation*

The goal of value function approximation in an ADP algorithm is to reconstruct the "true" Bellman Value function that would normally be calculated by an exhaustive SDP algorithm. Figure 6-11 illustrates the method of reconstructing a three-dimensional Bellman Value function from sampled points in ADP, compared to the original SDP-derived function. Unfortunately, due to the dimensionality of the problem under study and the computational time required to exhaustively search through all possible decisions, states, and uncertainties, creating the true Bellman Value surfaces via SDP is not a practical solution. Several approaches exist to approximate value functions, including linear and non-linear global regression, separable piece-wise linear approximation, and various non-parametric interpolation-based methods.

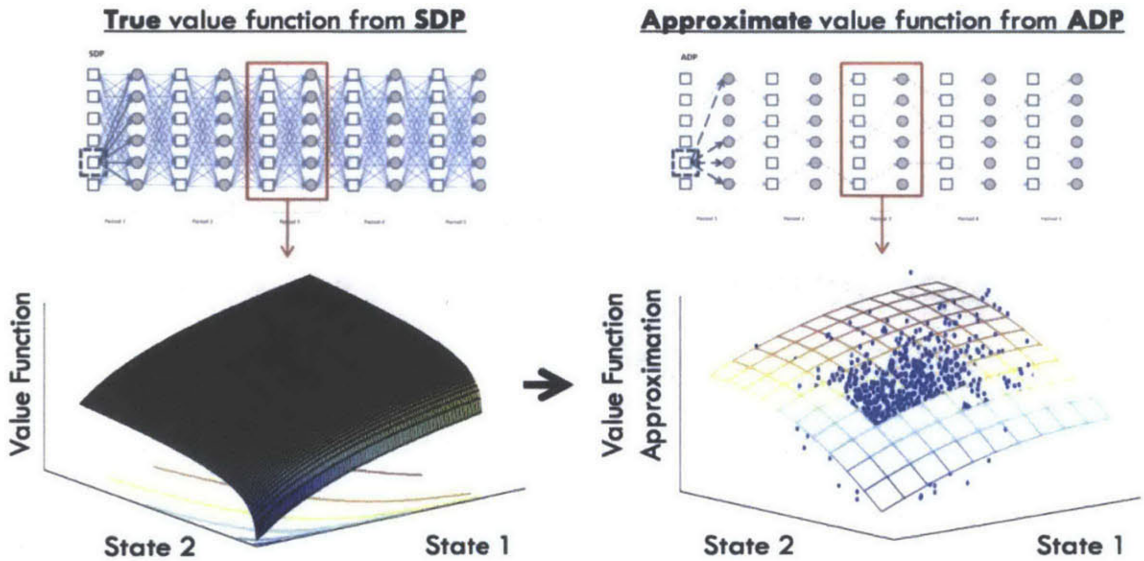


**Figure 6-11 Illustration of value function approximation via ADP, compared to the original value function from conventional SDP via backward induction [16]**

The approach used to approximate the value function in this study draws from the statistical interpolation literature, approximating the expected value of being in any state as a reduced-form function of key features. Because of the forward sampling, not all state variables required for backward induction are needed as the key features or basis functions (Bertsekas & Tsitsiklis, 1996). For this application, the fundamental structure is one of balancing near-term costs of R&D investment against long-term costs from installing capital-expensive power plants. Thus, in terms of the state variables described above, the key features needed to approximate the value function are the knowledge stocks for the emerging technologies wind and coal with CCS, $HEBACK_1(t)$ and $HEBACK_2(t)$, respectively.

The approach employed is a moving least squares (MLS) (Fasshauer, 2007) method to interpolate the value function at a given state within a specified neighborhood.

[16] A global (parametric) linear OLS regression was applied in the ADP illustration above.

Meshfree methods such as MLS have been applied to other problems requiring interpolation in high-dimensional space such as scattered data modeling, the solution of partial differential equations, medical imaging, and finance (Fasshauer, 2007). In the context of stochastic optimization, MLS was applied in Parpas and Webster (2011) in an iterative algorithm that solves for the stochastic maximum principle. In Webster, Santen, and Parpas (2012), it was applied in the context of the dynamic programming principle in a novel numerical decision under uncertainty problem for global climate policy.

The MLS approximation of the value function is:

$$\hat{v}_t(s) = \bar{\Phi}(s)\bar{r}(s) \qquad \text{(Equation 6.2.6)}$$

where $\Phi$ is a row vector of basis functions and $r$ is a column vector of coefficients that solves,

$$\min_{\bar{r}} \sum_{s_i} \left(\hat{v}_t(s_i) - \bar{\Phi}(s_i)\bar{r}(s_i)\right)^2 \qquad \text{(Equation 6.2.7)}$$

for sample states $s_i$ within some neighborhood of the state $s$. This method requires solving many "local" regressions over the course of a single run, one for each point to be interpolated in each decision period, during each iteration. However, these regressions are generally for a small number of samples in the immediate neighborhood, and therefore computation time is not compromised. Furthermore, the algorithm developed and applied here uses linear basis functions for each local regression, which has the advantage of approximating a large class of value functions, including those with multiple non-convexities where a parametric value function approximation approach may be challenging to apply. To store samples from all previous iterations and efficiently search for samples within a given neighborhood for the interpolation, a kd-tree data structure is used (Fasshauer, 2007). Figure 6-12 shows a representative surface of the Bellman Value function by the state variables, coal with CCS knowledge stock (*$HEBACK_1(t)$*) and wind knowledge stock (*$HEBACK_2(t)$*), for the second decision period from the stochastic model. Appendix D Part 2 presents results from validating the new ADP model.

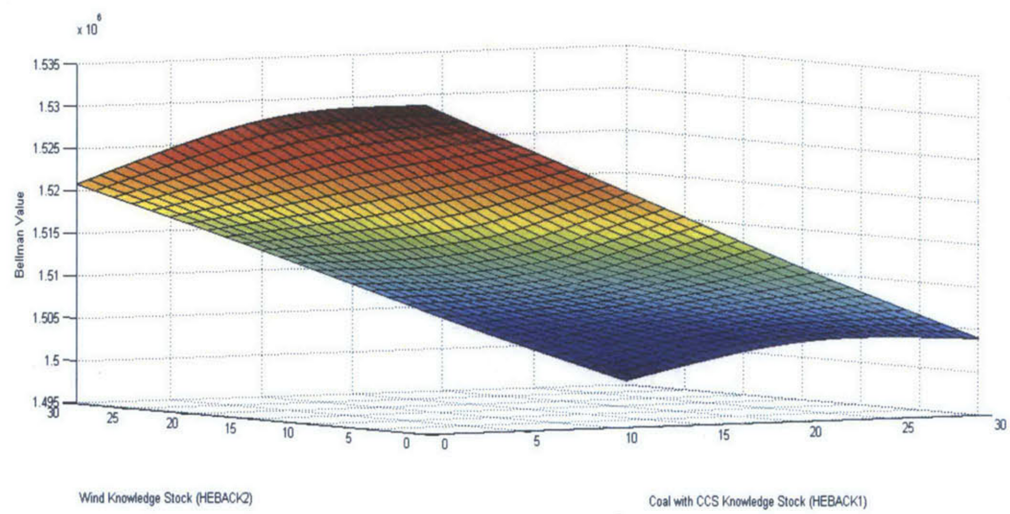


**Figure 6-12 Representative surface of Bellman Value function by state variables, coal with CCS knowledge stock (HEBACK1(t)) and wind knowledge stock (HEBACK2(t))**

The next chapter presents results from the stochastic modeling analysis, comparing the stochastic investment strategy to the deterministic strategy. It also discusses the effect of uncertainty level and distribution shape, and the effect of technology characteristics on the optimal investment strategy.

# Chapter 7 Investment Planning under Endogenous Technological Change Uncertainty: Results and Discussion

This chapter presents results from the stochastic investment planning model, described in Chapter 6. Three analyses are performed and discussed. In Section 7.1, results from solving the stochastic model with reference distributions for R&D efficiency are presented and compared to the optimal deterministic R&D investment strategies. In Section 7.2, the impact of applying empirically-motivated skewed distributions to represent the uncertainty in R&D efficiency is demonstrated. In Section 7.3, results from a sensitivity analysis investigating the impact of the overall level of risk (i.e., variance) in R&D efficiencies are presented. For reference, Table 7-9 at the end of the chapter summarizes the key assumptions and parameters that vary across the different analyses.

## 7.1 Reference Model: Optimal Investment Strategies with and without Uncertainty

The goal of the first stochastic analysis is to determine whether and how the optimal R&D investment strategy under technological change uncertainty differs from the optimal investment strategy determined under the assumption of perfect information. To answer this question, reference distributions for R&D efficiency for the two emerging technologies are assumed, and results from solving the stochastic model with and without this uncertainty are presented.

As described in Chapter 6, the reference version of the stochastic model is a 6-stage, 5-technology, cost-minimizing, long-term electricity generation R&D and capital investment planning model. To represent uncertainty about technological change and the ability to learn about uncertainty and revise decisions between stages, the planning problem is formulated as a formal sequential decision making problem under uncertainty, and numerically solved using approximate dynamic programming (ADP) techniques. The decision variables represent the amount of R&D investment into two emerging electricity generation technology categories—"coal with CCS" and "wind"; capital investment decisions are fixed in the current problem. Technological change uncertainty is represented as a multiplicative shock to an R&D investment "efficiency" parameter, which stimulates alternate plausible capital cost reductions in the emerging technologies. The reference stochastic model uses a Lognormal probability distribution to represent the uncertainty and skewness in R&D investment efficiency, with location parameter, $\mu = 0$ (mean adjusted so that the mean equals 1), and scaling parameter, $\sigma = 0.5$. The mean of 1.0 for the shock distribution ensures that the mean of the stochastic versions are identical to the deterministic versions. Optimal investment strategies are compared under two policy scenarios: a business-as-usual (BAU) carbon emissions scenario (no constraining cumulative carbon cap) and a 50% below BAU carbon emission scenario (analogous to the "moderate" cap in the Chapter 4 and 5 deterministic analyses). For comparison, the deterministic optimal investment strategy is also solved for, by applying a Normal distribution and reducing the variance close to zero.

### *7.1.1 Deterministic Optimal Investment Strategy*

To approximate the deterministic investment strategy, uncertainty is "removed" in the ADP model by applying a Normally-distributed multiplicative shock to the R&D investment efficiency parameter with a mean = 1.0 and very small standard deviation (0.01). (Results from validating the ADP model are given in Appendix D Part 2).

Figure 7-1a shows the optimal deterministic investment strategy under BAU, and the associated optimal generation capacities are shown in Figure 7-1b. Figures 7-2a and 7-2b show results from the 50% below BAU carbon cap scenario. Tables 7-1 and 7-2 provide the values associated with these graphs. For discussion purposes, Table 7-3 displays the new capacity additions to the system under each cap.

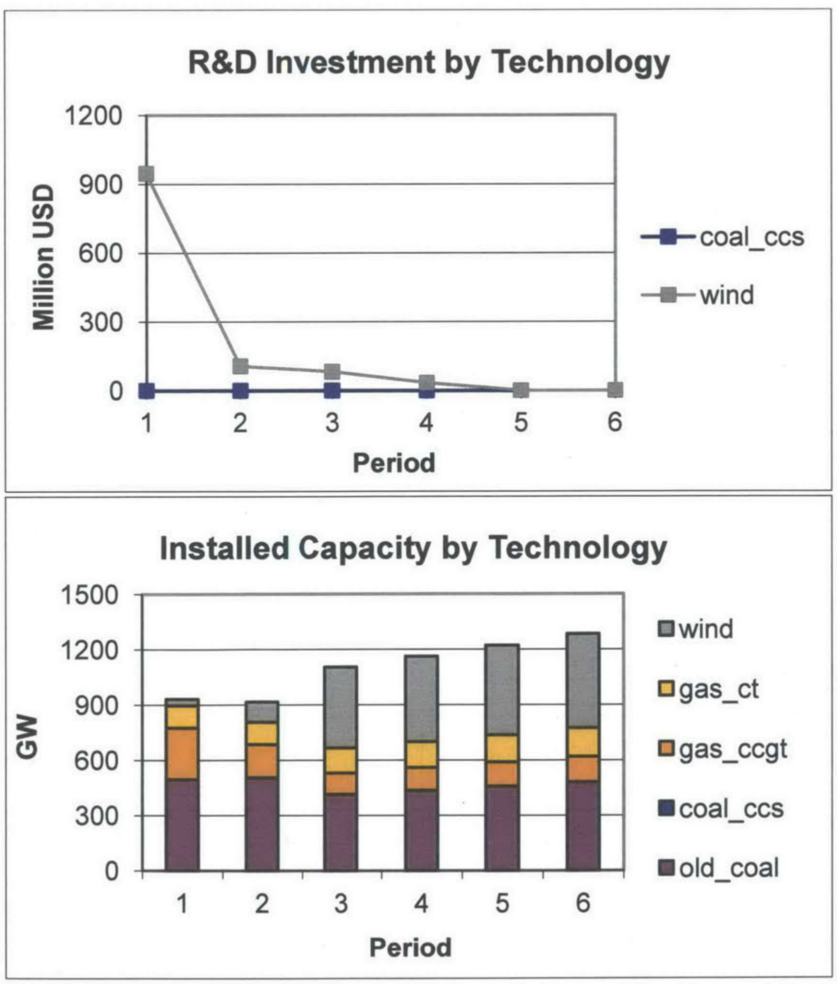


**Figure 7-1 Optimal R&D investments (top) and installed capacities (bottom) by technology under BAU**

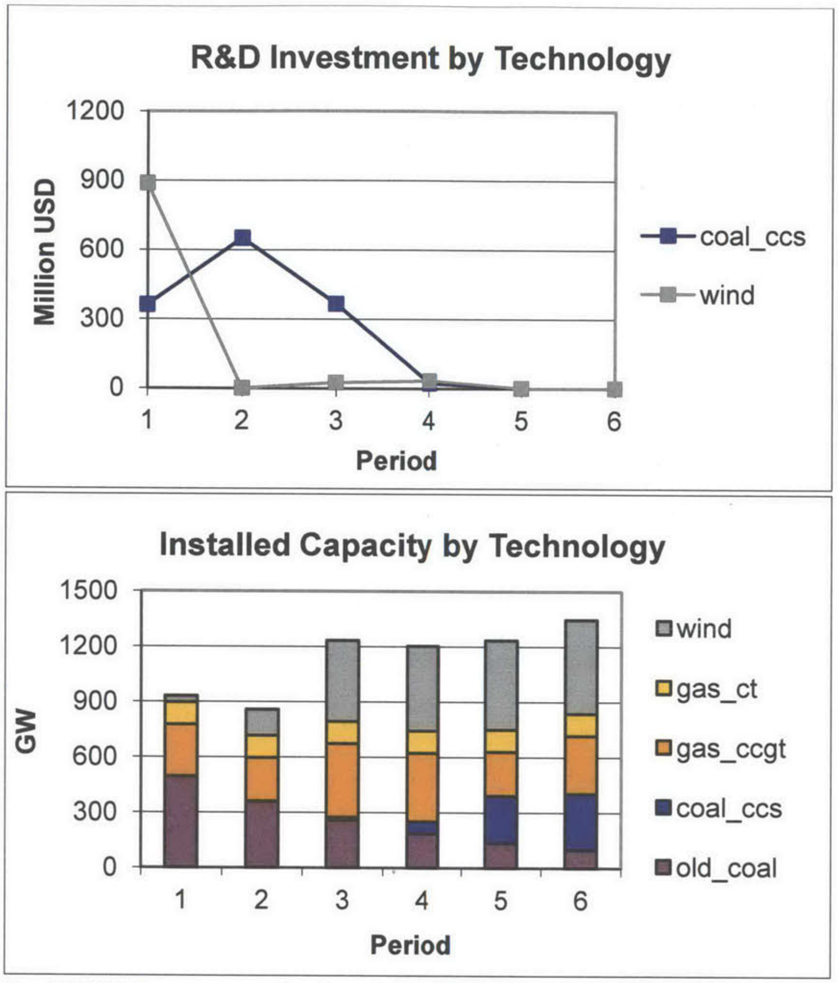


**Figure 7-2 Optimal R&D investments (top) and installed capacities (bottom) by technology under a CARBON TARGET (50% BAU). *Note wind R&D investment is based on the second y-axis.**

**Table 7-1 R&D Investments (in Million USD) by Technology, Period, and Carbon Target**

| Technology / Period | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **BAU (No Carbon Cap)** | | | | | | |
| *Coal with CCS* | 0 | 0 | 0 | 0 | 0 | 0 |
| *Wind* | 946.36 | 106.60 | 81.60 | 33 | 0 | 0 |
| **50%BAU Carbon Cap** | | | | | | |
| *Coal with CCS* | 361.32 | 650.28 | 365.72 | 22.24 | 0 | 0 |
| *Wind* | 887.52 | 0 | 24.72 | 33.12 | 0 | 0 |

**Table 7-2 Installed Capacity (in Gigawatts) by Technology, Period, and Carbon Target**

| Technology / Period | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **BAU (No Carbon Cap)** | | | | | | |
| *Coal with CCS* | 1 | 1 | 1 | 1 | 1 | 1 |
| *Wind* | 35.30 | 109.72 | 438.88 | 461.32 | 484.91 | 509.71 |
| **50%BAU Carbon Cap** | | | | | | |
| *Coal with CCS* | 1 | 4 | 16 | 64 | 256 | 305.83 |
| *Wind* | 35.230 | 141.18 | 438.88 | 461.32 | 484.91 | 509.71 |

**Table 7-3 NEW Capacity Additions (in Gigawatts) by Technology, Period, and Carbon Target**

| Technology / Period | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| **BAU (No Carbon Cap)** | | | | | | |
| *Coal with CCS* | 0 | 0 | 0 | 0 | 0 | 0 |
| *Wind* | 74.42 | 329.16 | 22.44 | 23.59 | 24.80 | 0 |
| **50%BAU Carbon Cap** | | | | | | |
| *Coal with CCS* | 3 | 12 | 48 | 192 | 49.83 | 0 |
| *Wind* | 105.89 | 297.69 | 22.44 | 23.59 | 24.80 | 0 |

There are two structural assumptions of the model that are important to understand these and all of the following analyses. First, new generating capacity is built and paid for at time period, $t$, but does not appear as part of the installed capital base and become operational until time $t+1$. Second, R&D investments at time $t$ result in capital cost reductions at time $t+1$ (costs in the first period are fixed at their initial capital costs).

Under BAU (no carbon cap), the optimal strategy is to invest in R&D only in wind, and at a relatively aggressive amount ($945M) (Figure 7-1a). The aggressive R&D investment in wind in the first period is optimal because of the dramatic wind deployment plan in Period 3. While a portion of wind is built in the first and other periods, the majority (329 GW) of the total 475 GW is built in the second period. Thus, wind R&D investment is aggressive in the first period in order to reduce capital costs in the second period. Wind R&D continues at a lower level through Period 4, when it reaches its lowest point ($33M). This continued R&D investment in wind matches the continued (lower) deployment in later periods. Overall, the majority of wind capacity investments (and thus R&D investments) take place in early periods, despite the option of building it later. This result is explained by the relatively low capital and fuel costs for wind to begin with, compared with other technologies (discussed in detail in Chapters 4 and 5). Coal with CCS plays no role in the physical system under BAU, and is thus allocated zero R&D funds.

Under a carbon emissions target (50% below BAU), two changes are seen in the optimal R&D investment strategy relative to the strategy without a carbon cap, and driven by the changes seen in the capacity mix. First, $360 million is invested in coal with CCS in the first period, in order to begin building the knowledge stock and reducing capital costs before large coal with CCS deployments in later periods. This R&D continues through Period 4, increasing and then decreasing, to continue reducing capital costs. The more gradual R&D investment in coal with CCS technology is attributed to the more gradual addition of coal with CCS technology in the system (compared to wind). Second, wind R&D investment in the first-period is reduced slightly from the BAU scenario, from $945M to $880M, and dramatically declines in the next three periods. This can be explained by noting the shift of the timing of wind deployment in this scenario. To meet the more stringent cumulative emissions target, more zero-emission wind power needs to be deployed and operational during the second period, which requires it to be built during the first period, before R&D investments can alter the capital costs. Thus, wind R&D investment is reduced in the first period, in line with the fact that less wind capacity is being built in the period after capital cost reductions will have taken place.

### *7.1.2 Stochastic Optimal Investment Strategy*

The decision problem under uncertainty is modeled by applying the reference mean-adjusted Lognormal distribution of the shock ($\mu = 0$; $\sigma = 0.5$) to the R&D investment efficiency parameter. Mean adjusting the shock distribution to 1.0 ensures that the original mean R&D efficiency parameter is preserved, while still allowing for uncertainty and skewness in R&D returns. Table 7-4 provides the values for the deterministic and stochastic first-period optimal strategies, for comparison, and a summary of these results under the two carbon scenarios are shown in Figures 7-4. In the stochastic model, the optimal investment strategy for the second through sixth period is a distribution of investments, which are conditional on the "state of the world" in that time period. Thus, for these periods, the distribution of optimal strategies is shown (with a bar that marks the 5$^{th}$ and 95$^{th}$ percentiles of the optimal strategy), and compared with the deterministic optimal strategy (Table 7-5 and Figure 7-5 and 7-6).

**Table 7-4 Stochastic v. Deterministic Optimal First-Stage Investment Strategy (in Millions USD)**

| Technology | Stochastic | Deterministic | *Difference* |
|---|---|---|---|
| **BAU (No Carbon Cap)** | | | |
| *Coal with CCS* | 0 | 0 | ***0** (0%)* |
| *Wind* | 1146 | 946 | ***+200** (+21%)* |
| **50% BAU Carbon Cap** | | | |
| *Coal with CCS* | 230 | 361 | ***-131** (-36%)* |
| *Wind* | 857 | 888 | ***-31** (-3%)* |

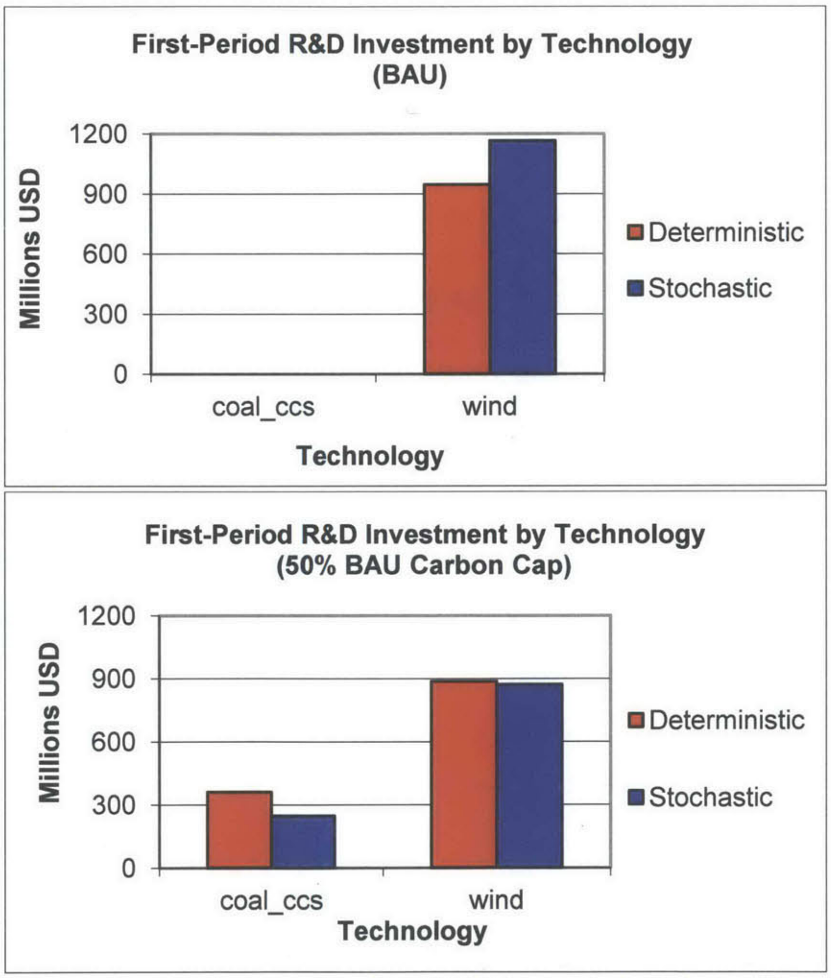


**Figure 7-3 Comparison of first-period optimal R&D investment strategy with and without uncertainty under BAU (top) and 50% BAU Carbon Cap (bottom)**

**Table 7-5 Distribution of Stochastic v. Deterministic Optimal Investment Strategies Periods 2-6 (in Million USD)**

| Period | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| ***Coal with CCS*** | | | | | |
| **BAU** | | | | | |
| Deterministic | 0 | 0 | 0 | 0 | 0 |
| Stochastic (p05) | 0 | 0 | 0 | 0 | 0 |
| Stochastic (p50) | 0 | 0 | 0 | 0 | 0 |
| Stochastic (p95) | 0 | 0 | 0 | 0 | 0 |
| **50% Cap** | | | | | |
| Deterministic | 650 | 366 | 22 | 0 | 0 |
| Stochastic (p05) | 111 | 48 | 0 | 0 | 0 |
| Stochastic (p50) | 302 | 224 | 0 | 0 | 0 |
| Stochastic (p95) | 835 | 580 | 36 | 0 | 0 |
| ***Wind*** | | | | | |
| **BAU** | | | | | |
| Deterministic | 107 | 82 | 33 | 0 | 0 |
| Stochastic (p05) | 20 | 20 | 20 | 0 | 0 |
| Stochastic (p50) | 52 | 40 | 20 | 0 | 0 |
| Stochastic (p95) | 137 | 104 | 52 | 0 | 0 |
| **50% Cap** | | | | | |
| Deterministic | 0 | 25 | 33 | 0 | 0 |
| Stochastic (p05) | 0 | 0 | 19 | 0 | 0 |
| Stochastic (p50) | 0 | 36 | 24 | 0 | 0 |
| Stochastic (p95) | 0 | 96 | 56 | 0 | 0 |

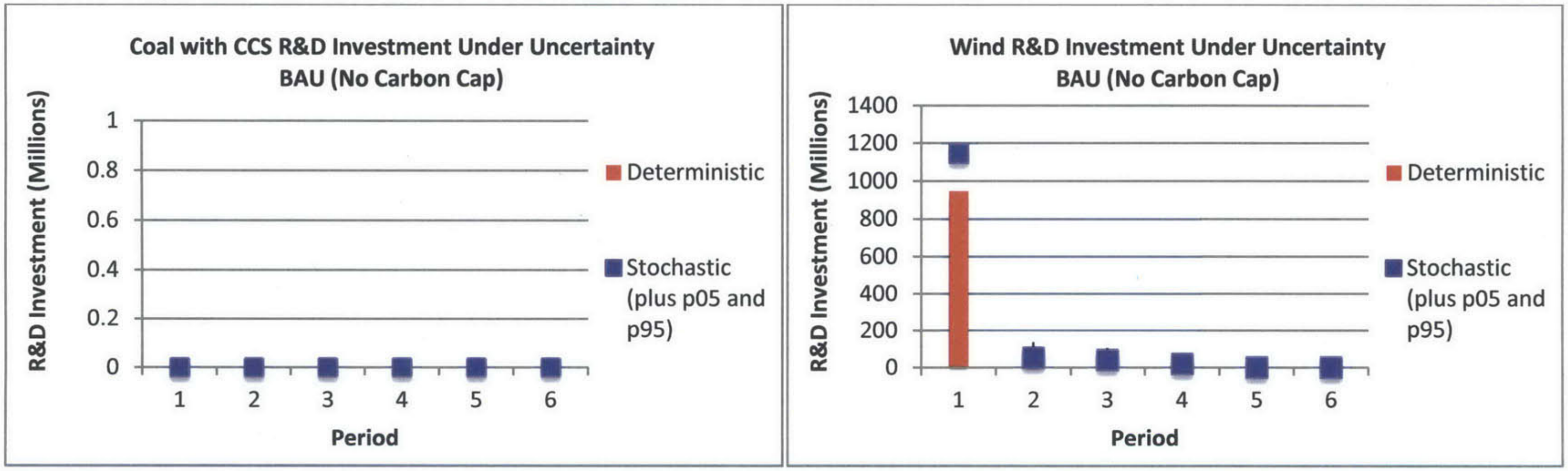


**Figure 7-4 Optimal R&D investment strategies with and without uncertainty under BAU for Coal with CCS (left) and Wind (right)**

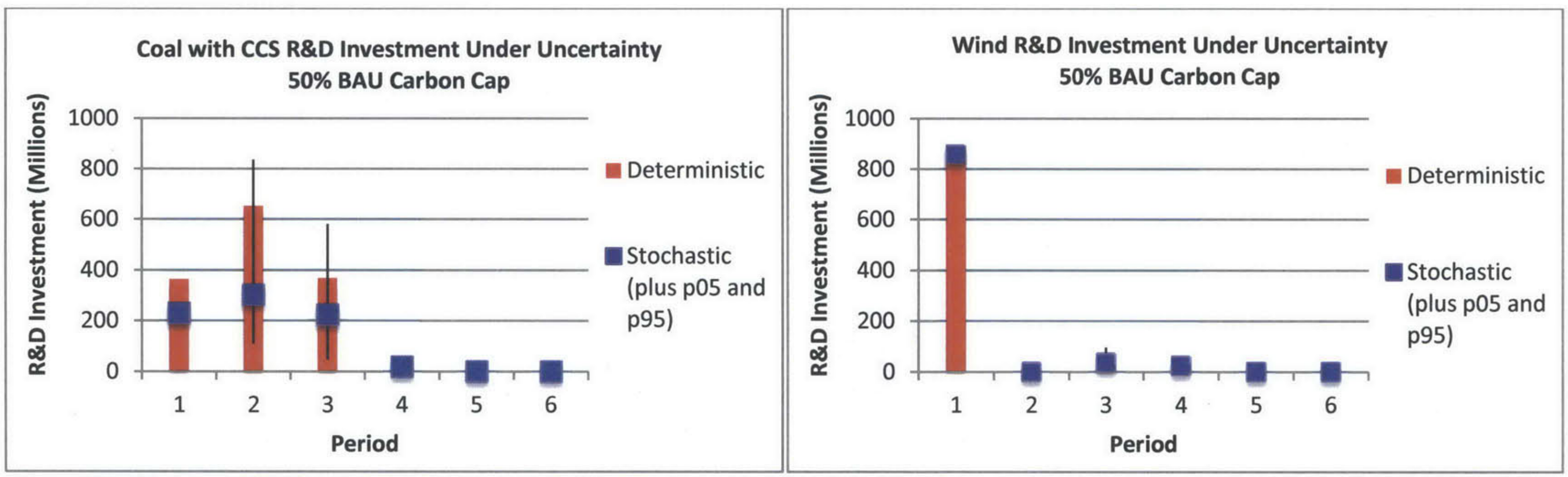


**Figure 7-5 Optimal R&D investment strategies with and without uncertainty under a 50% BAU Carbon Cap for Coal with CCS (left) and Wind (right)**

Under technological change uncertainty, the optimal near-term (first-period) R&D investment strategy can be different than the optimal deterministic strategy. The direction and magnitude of the change in strategy depends upon the technology and the timing of new capacity deployment.

Under BAU, the optimal first-period wind R&D investment strategy under uncertainty is over 20% higher than under the assumption of perfect information (Figure 7-4a). Future period decisions are conditional on new "states of the world," with respect to observed technological change and previous R&D investment decisions, but as Figure 7-5b shows, after the first period, the median stochastic investment strategy follows the deterministic investment strategy closely. The first-period R&D increase is attributed to the very large wind capacity additions in Period 2. Under BAU, the majority of new wind capacity is added in Period 2, with only small new additions occurring in other periods. Thus, the decision maker in this situation has a single "chance" to take advantage of the potential increased R&D returns under uncertainty. Small corrections in the event of low returns can then be made in later decision periods. Coal with CCS R&D investment does not experience any changes under BAU, as it does not play a role in the system under this carbon target and therefore has no R&D investments.

Under a carbon cap, the wind R&D investment change (decrease) under uncertainty decreases to within 3% of the deterministic strategy. In this scenario, the difference is not significant, and is an artifact of the minor variability that is inherent to the ADP method. The pattern of R&D investment behavior in this scenario is also driven by the timing of new capacity deployment, and provides intuition about the direction and magnitude of the change. The decrease in investment under uncertainty is due to the changing deployment pattern over time for wind across the carbon target. Under the carbon target, new wind capacity (an additional 30 MW compared to BAU) is added in Period 1, before R&D investments can affect capital costs. Thus, there is less incentive to spend more towards R&D, even under uncertainty. Table 7-5 and Figure 7-5b shows that in later decision periods, the distribution of optimal investment strategies includes the possibility of increasing R&D, which would occur if observed technological change had been high and the previous decision not to increase R&D had taken place.

With respect to R&D investment in coal with CCS, the first-period optimal investment under uncertainty is 36% less than the deterministic investment (Figure 7-4b). This is attributed to the later period deployment plan for coal with CCS under this carbon target (Table 7-4). The majority of new coal with CCS capacity is added in Periods 3 through 5, allowing for time to observe the rate of technological change for some time before large investments have to be made. Thus, the optimal strategy involves decreasing R&D investment in the near term, in order to wait and learn before future decisions have to be made. Figure 7-6a illustrates this pattern of decreased investment continues through Period 2, after which the median of the distribution of optimal investments includes investing the same or more as the deterministic strategy. It is also noteworthy that coal with CCS R&D investment *does* in fact still take place beginning in the first period, even though the majority of deployment does not take place until later periods. The reason for this is because of the path dependent nature of the problem. Early R&D investment begins building the technology knowledge stock base, which allows one to take advantage of even larger capital cost reductions in future periods in the case of high returns.

The results from this analysis provide two key insights. Overall, when uncertainty and learning are formally considered in the electricity R&D investment planning problem, the optimal near-term strategy can be different than the optimal strategy determined under perfect foresight. However, *when* a technology is needed to meet a particular carbon target—defined by the specific role the technology plays and how it interacts with other technologies on the system to reliably meet electricity demand—dictates whether a change in strategy from the deterministic case is optimal, and if so what the direction and magnitude of the change is. When the technology is required in bulk in the near term, and there will be fewer opportunities for R&D to build the knowledge stock and decrease total costs in the future, the incentive is to increase R&D. However, when the technology is required further in the future, there is greater incentive to decrease near-term investment and "wait and see" technological change outcomes. These two results are important because they reveal that the amount and timing of deployment for emerging technologies in the physical system affect the level of innovative effort that should be taken on their behalf.

## 7.2 Effect of Skewness on Optimal Investment Strategy under Uncertainty

The next analysis is motivated by the empirical literature on technological change showing that outcomes to the innovation process are not only uncertain, but that they are highly right-skewed, with frequent opportunities for low-return outcomes and rare opportunity for high-return outcomes (See Chapters 3 and 6). This analysis explores the specific effect on the optimal R&D investment strategy under uncertainty if the emerging technologies follow an uncertain R&D efficiency pattern similar to the skewed distributions found in the literature. To test this, an exponentially-distributed shock with $\lambda = 1$ is applied to the R&D efficiency parameter, and compared to when it follows a Normally-distributed shock with $\mu = 1$ and $\sigma = 1$. These distributions have identical means and variances, and differ only in the skewness. The Normal distribution has a skewness of zero, while the exponential distribution with $\lambda = 1.0$ has a right skewness value of 2.0. Figure 7-7 compares the two distributions applied. Optimal R&D investment strategies are studied under the two carbon scenarios (BAU and 50% BAU), and results from the exponentially-distributed versus Normally-distributed R&D efficiencies are compared.

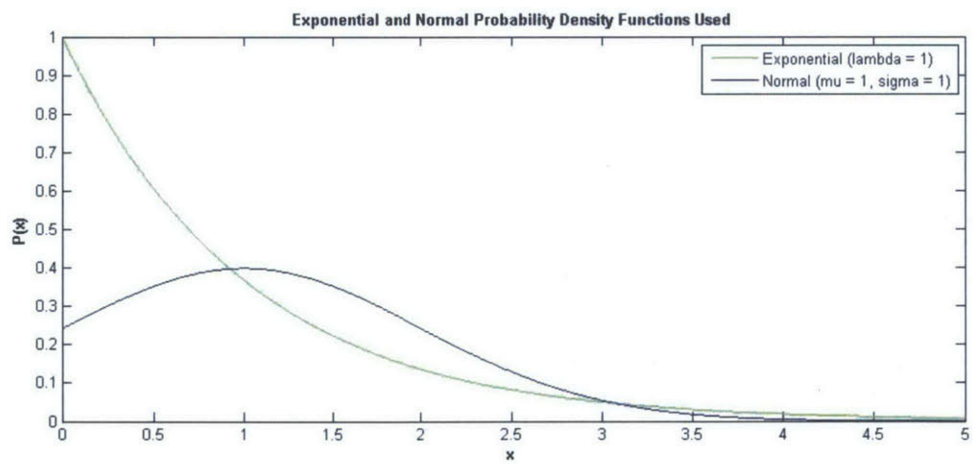


**Figure 7-6 Normal and Exponential probability distributions used to represent "shocks" to R&D investment efficiency with and without skewnesss**

Table 7-6 and Figure 7-8 present the results of the optimal first-period R&D investment strategies under the exponential PDF and under the Normal PDF.

**Table 7-6 Optimal First-Period R&D Investments under Different R&D Efficiency Profiles (in Million USD)**

| Carbon Scenario | Normal PDF $\mu = 1; \sigma = 1$ | Exponential PDF $\lambda = 1.0$ | **Investment Decrease from Normal to Exponential** |
|---|---|---|---|
| **BAU (No Cap)** | | | |
| *Coal with CCS* | 0 | 0 | **0** |
| *Wind* | 1246.48 | 1124.84 | **121.64 (9%)** |
| **50% BAU Carbon Cap** | | | |
| *Coal with CCS* | 387.44 | 316.04 | **71.40 (18%)** |
| *Wind* | 1032.44 | 852.96 | **179.48 (17%)** |

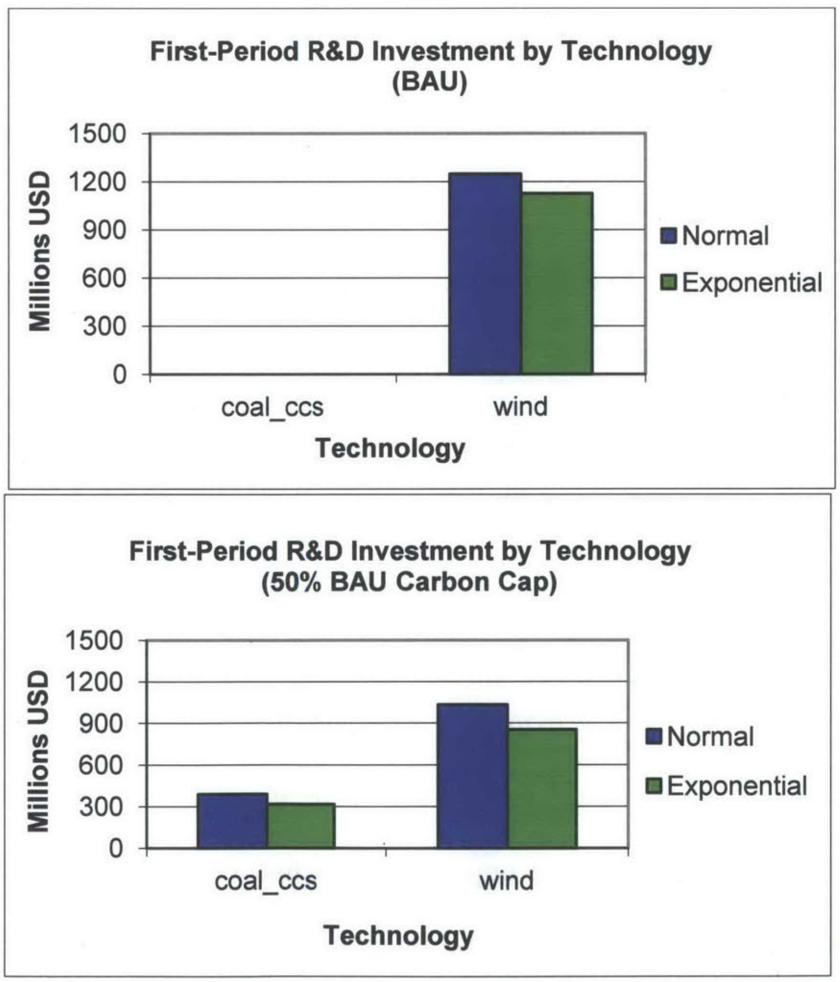


**Figure 7-7 Optimal First-Period R&D investments for different R&D efficiency profiles under BAU (top) and a 50% BAU Carbon Cap (bottom)**

Under BAU, coal with CCS does not play a role in the physical system (i.e., no capacity is added). Therefore, optimal R&D investments remain at zero across both risk profiles. However, under a carbon target, introducing skewness in the uncertainty (more opportunity for lower returns but rare opportunity for very high rewards) results in an almost 20% reduction in near-term R&D investments compared to that under symmetric uncertainty (Table 7-6 and Figure 7-8b). Following from the discussion in Section 7.2, the timing of new capacity additions plays a role in explaining this behavior. Under a carbon target, the majority of coal with CCS deployment is in the later periods. Thus, there is abundant opportunity to influence its capital costs through early R&D investments. This strong learning-by-searching (LBS) pathway to reduce its capital cost exposes the R&D effort to the uncertainty, and with more frequent opportunities for low-return, there is an incentive to decrease the amount invested upfront (and avoid potential losses). This pattern of incentive to decrease investment under skewed distributions continues throughout future periods as well. While there is an opportunity to learn and revise between decision periods, the median optimal investment tendency is to reduce R&D investment compared to the optimal strategy under symmetric uncertainty.

The effect of skewness on the optimal investment strategy for wind is also to decrease near-term R&D by approximately 10% and 20%, under the BAU and a carbon cap, respectively (Table 7-6 and Figure 7-8). As is the case with coal with CCS, the introduction of skewness and more opportunity for low returns to R&D decreases the optimal investment strategy compared to a more symmetric risk. Moreover, the smaller amount of wind R&D investment that takes place under the carbon cap (due to more wind capacity being added in the first period), allows the decrease in R&D under a skewered uncertainty to be more pronounced. This is directly analogous to the changes in R&D investment seen in the first analysis on optimal investment strategy under uncertainty and no uncertainty. Under uncertainty and a carbon cap, the first period wind R&D investment was less than under BAU because there was less benefit to receive from investing in first-period R&D. Here, R&D investment in the first period incentives an even greater reduction in investment when the opportunity to receive high valued returns is lower.

Overall, this analysis provides an example that right-skewed uncertainties such as those experienced in the innovation process can result in incentives to reduce R&D spending when compared to symmetric uncertainties. The timing of technology deployment in the system and the opportunity to learn in later periods, determines the magnitude of these changes. Additionally, the analysis highlights the value of using a formal stochastic decision model to study the effect of risk profiles on the optimal investment strategy under uncertainty and learning. A common assumption might be that with less frequent opportunities for high returns, the best investment decision is to *increase* near-term R&D in order to try and increase the chances of obtaining a good outcome. However, this analysis shows that in the presence of such skewed uncertainty, the optimal decision is to take "small steps" and wait and see about interim technological change.

## 7.3 Effect of Overall Level of Risk on Optimal Investment Strategy

The final experiment explores the impact of the overall level of uncertainty (risk) in technological change on the optimal investment strategy. The first analysis demonstrated that the introduction of uncertainty in R&D efficiency with a moderate variance and skewness can cause either a decrease or increase in the optimal hedge against uncertainty, depending on the timing of a technology's capacity deployment plan. The second analysis investigated the specific impact of skewness of the R&D outcomes on the optimal investment strategy, holding the mean and spread constant between two distributions tested. That analysis shows that right-skewness creates an incentive to decrease near-term R&D when compared to a symmetric uncertainty. In this section, the impact of increasing levels of variance on the optimal investment strategy is studied. Increasing variance represents a wider spread of the risk—more frequent R&D outcomes that are higher or lower than the average. The goal of this analysis is to investigate whether the characteristic of overall risk level impacts the optimal investment strategy under uncertainty, and how this impact may differ across technology types.

Once again, optimal investment strategies under BAU and a 50% BAU cumulative carbon target are compared. The risk level is explored by applying Beta distributed shocks with scale parameters $(\alpha, \beta)$ = (1, 4), (2, 8), (4, 16), and (8, 32) and means of 1.0, to the reference (deterministic) R&D efficiency parameter for each emerging technology[17]. First-period results are shown in Table 7-7, followed by Figure 7-8 and Figure 7-9.

[17] The corresponding variance levels for these distributions are 0.0267, 0.0145, 0.0076, and 0.0039, which represents changes in variance of approximately a factor of 2. These distributions also have small changes in skewness, but skewness changes by a much smaller amount (approximately 25%).

**Table 7-7 Optimal First-Stage Investment Strategy under Varying Risk Levels (in Million USD)**

| Technology | Beta(1.4) Variance = 0.0267 | Beta(2,8) Variance = 0.0145 | Beta(4,16) Variance = 0.0076 | Beta(8,32) Variance = 0.0039 |
|---|---|---|---|---|
| **BAU (No Carbon Cap)** | | | | |
| *Coal with CCS* | 0 | 0 | 0 | 0 |
| *Wind* | 1139 | 1177 | 1150 | 1042 |
| **50% BAU Carbon Cap** | | | | |
| *Coal with CCS* | 20 | 74 | 241 | 350 |
| *Wind* | 907 | 861 | 862 | 875 |

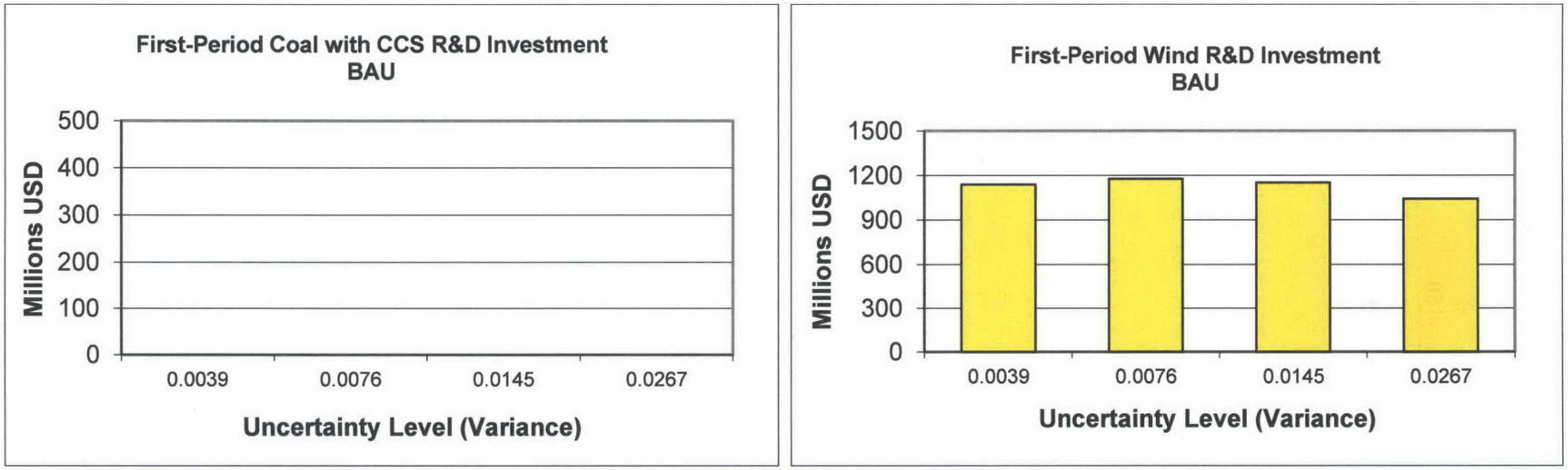


**Figure 7-8 Optimal first-stage R&D investment strategies by level of uncertainty under BAU for Coal with CCS (left) and Wind (right)**

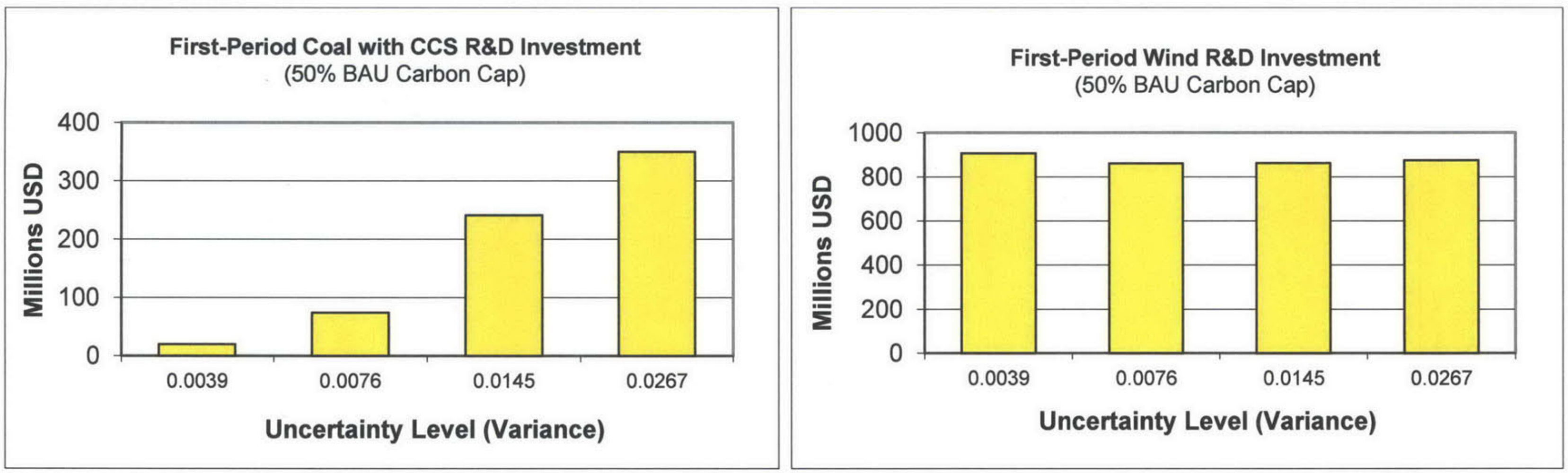


**Figure 7-9 Optimal first-stage R&D investment strategies by level of uncertainty under 50% BAU for Coal with CCS (left) and wind (right)**

The results for coal with CCS R&D investment across uncertainty levels and carbon caps will be discussed first. As usual, under BAU there is no R&D investment in coal with CCS, because it will not be deployed without a carbon emissions cap. However, under a carbon cap the optimal R&D in coal with CCS increases as uncertainty in R&D efficiency increases (Figure 7-9 above). Moreover, the optimal investment strategy is quite sensitive to changes in the variance. This is due to the delayed nature of coal with CCS capacity deployment and therefore there is abundant time to learn and observe interim technological change. The potential for increased high returns from the increased spread creates an opportunity to start (aggressively) building the knowledge stock base for coal with CCS early, which can help reduce capital costs substantially by the time most of the technology needs to be deployed. "Corrections" to the aggressive near-term R&D are then made in later decision periods as additional information about the technological change uncertainty is collected. Therefore, the more likely a first-period high R&D return is, the more worthwhile it is to invest big early in coal with CCS.

The optimal first-period R&D investment in wind under both BAU and the 50% carbon cap remains relatively insensitive across overall risk levels (Figure 7-8 andFigure 7-9). The small differences seen are again an artifact of the minor variability inherent in the ADP method. This insensitivity can be explained by the results of the previous analyses, which demonstrate that the timing of capacity deployment and (lack of) opportunity to learn and revise decisions over time influence the optimal R&D decision paths. Again, the upfront nature of the wind capacity deployment plan creates an incentive to invest heavily upfront in wind R&D, but leaves little room for learning and revising in later periods. Without this opportunity to learn in the interim before large capital deployments and "correct" previous decisions, the incentive to increase near-term R&D in the hopes of applying it to a high return rate (and begin building a knowledge stock) does not exist. The lower overall R&D magnitudes under the 50% BAU carbon cap are also witnessed in this analysis. This is expected given the shift in additional wind capacity additions to Period 1 before R&D investments can alter costs.

To summarize the key findings in this analysis, the optimal near-term R&D investment strategy for a given technology tends to increase with the overall risk level (i.e., variance). However, the size of the increase is based on the 1) the capacity deployment plans of the respective technologies, and 2) the overall opportunity or lack of opportunity to learn and revise decisions over time (and potentially begin building a large knowledge stock base). In the case of wind power, for example, the lack of opportunity to learn about uncertainty and revise decisions creates a negligible change in R&D investments across different levels of risk. Overall, the main result from this analysis is that at increasingly high variance levels where the opportunity to benefit from high returns grows, the incentive is to take the "chance" to begin building a large knowledge stock base early, and correct in future decision periods if necessary.

**Table 7-8 Model Assumptions and Parameter Definitions for Stochastic Model Analyses**

| Section No. | Analysis Name | Corresponding Parameter and Reference Value | Analysis Parameter Value(s) | Notes |
|---|---|---|---|---|
| **Section 7.1** | Reference Model: Optimal Investment Strategies with and without Uncertainty | $\theta_g \sim N$ (μ=1,σ=0.01)* | $\theta_g$ ~*LN* (μ=0,σ=0.5) | * θ is the multiplicative shock applied to β, the R&D efficiency parameter of the "Innovation Possibilities Frontier (IPF)"<br>The Normal PDF with small variance approximates the deterministic solution. |
| **Section 7.2** | Effect of Skewness on Optimal Investment Strategy | $\theta_g \sim N$ (μ=1,σ=1) | $\theta_g$ ~ *Exp* (λ=1) | |
| **Section 7.3** | Effect of Overall Risk Level on Optimal Investment Strategy | N/A | $\theta_g$ ~ *Beta*(α=1,β=4)**<br>$\theta_g$ ~ *Beta*(α=2,β=8)**<br>$\theta_g$ ~ *Beta*(α=4,β=16)**<br>$\theta_g$ ~ *Beta*(α=8,β=32)** | * Mean = 1.0; Variance = 0.0267, 0.0145, 0.0076, 0.0039, respectively (by a factor of approximately 2).<br>Skewness also changes across these parameters, but at a much slower rate (approxitmately 25%). |

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# Chapter 8 Conclusion

This chapter presents final remarks on the dissertation and its findings. Section 8.1 reviews the purpose of the dissertation and its contributions, summarizing the key insights from the analyses performed as they relate to the research questions posed at the beginning. Section 8.2 discusses the implications of the results for policy, emphasizing the role that quantitative modeling can play in informing energy and climate policy. Section 8.3 states the main limitations of the new quantitative modeling framework. Finally, Section 8.4 lists several opportunities for future research.

## 8.1 Dissertation Summary

This dissertation has presented a new decision support framework that enables quantitative analysis of socially optimal R&D and capital investment decisions for the electric power generation sector. Effective management of long-term problems such as climate change will require decisions about technology adoption and new technology development in this high carbon-emitting energy sector. The long infrastructure lifetimes of power plant investments mean that deployment decisions made today will influence carbon-dioxide emissions far into the future. Additionally, new technology development and R&D decisions can help reduce the overall costs of mitigating emissions, but there are multiple technology investments to choose among and returns to R&D are inherently uncertain. These features of the "deployment versus development" question create unique challenges for policy makers charged with managing cumulative carbon-dioxide emissions for the electric power generation sector.

Motivating this dissertation is that at present, national-scale electricity generation capacity expansion models can evaluate several aspects of the interaction between environmental policies and the electric power industry, but ultimately lack one or more of three overarching features jointly necessary to provide useful insights about an optimal balance between R&D program and power plant investments. The models lack (1) resolution of the critical structure of the electricity sector, (2) an explicit endogenous representation of the effects of learning-by-searching technological change, and/or (3) an efficient decision-analytic framework to explore technology investment options under a range of uncertain technology futures.

The new modeling approach presented here explicitly accounts for the complementary roles that generating technologies play within the electric power system, the physical integration constraints they face, and the economics at play in electric utilities' least-cost investment decisions, given the economics of technological change. A stochastic version of the model enables consideration of the characteristics of the uncertainty in technology innovation, and identifies flexible, adaptive R&D strategies for decision makers to consider. Together, these features of the modeling framework help reveal insights for technology deployment and development decision making, and thus carbon emissions reduction, in this unique sector.

### *8.1.1 Summary of Key Insights*

A set of analyses using both deterministic and stochastic versions of the new model yielded answers and insights to the three research questions posed at the beginning of the dissertation.

**Question 1: What is the optimal intra- and inter-temporal balance between electricity generation capital investments and R&D investments under technological change uncertainty?**

Under a specific cumulative carbon emissions reduction target, generation capital investment plans are determined by the relative cost and performance features of individual technologies, and their potentials for learning-by-doing. For example, under a business-as-usual carbon scenario (no emissions cap), the optimal strategy involves building abundant new conventional technologies such as coal plants to fill the "baseload" of electricity demanded, new natural gas plants to fill "shoulder" and "peak" loads, and new wind power plants to fill electricity demands at all levels. Each of these technologies has relatively inexpensive capital costs. However, under more stringent carbon scenarios with carbon emission caps, the optimal strategy involves focusing on new low-carbon coal with CCS plants and new zero-carbon nuclear plants to fill the baseload (where generous carbon reduction opportunities can be achieved). In general, capital investment decisions for building these initially expensive "emerging" baseload technologies are delayed until later periods to comply with their scale-up constraints, and once more cost reductions from learning-by-doing have been achieved.

For a specific carbon target, R&D investment strategies track generation capital investment needs. Under technological change uncertainty, the optimal R&D investment strategy is to assign aggressive amounts of R&D upfront to emerging technologies that need to be deployed in the near term. This is the case for technologies such as wind power across all carbon reduction targets. The initially low costs associated with wind power encourage its early deployment so that it can begin to help meet cumulative carbon targets. Subsequently, this early deployment encourages R&D investments in the near-term when reductions in capital costs can still benefit total system costs. For technologies that will not be deployed until later, the optimal strategy is to invest less in R&D in the near-term, and wait and learn about technological change outcomes before investing later. This is seen in the case of technologies such as coal with CCS technology. Coal with CCS plants have high initial capital costs, encouraging modest near-term R&D and higher future R&D (to take advantage of discounting and the combined effect of learning-by-doing). Under technological change uncertainty, this deployment pattern incentivizes a "wait and see" rule with respect to learning-by-searching.

**Question 2: How does the optimal investment strategy under uncertainty compare to the deterministic investment strategy design?**

A key motivation for this dissertation is the lack of current decision support models that appropriately consider uncertainty and learning in long-term planning for energy and environmental issues. As discussed in detail in Chapter 3, most current quantitative decision making tools rely on either 1) deterministic structures and Monte Carlo analyses or scenario-based analysis, which does not consider learning between decision periods, or 2) stochastic structures with low resolution in the number of time periods, decisions, and uncertainties, to manage dimensionality burdens. In this dissertation, a six-period stochastic sequential decision making model is presented, having the ability to make multiple technology R&D decisions under technological change uncertainty, with learning and revising between decision periods. The second research question above is posed to verify that the new sequential decision under uncertainty modeling platform provides additional valuable information to the decision maker over current modeling tools.

Results reveal that compared to the optimal deterministic investment strategy, the optimal strategy under moderate technological change uncertainty is to *increase* near-term R&D investment for technologies that need to be deployed in early periods, and *decrease* near-term R&D investment for technologies where the "wait and see" rule applies. This is seen in the case of wind and coal with CCS technologies in the analyses above. Given the low-cost characteristics for wind technology, early deployment of wind plants is encouraged. Under uncertainty, as there is only minimal time to benefit from potential high R&D returns (and less time to learn and revise), the incentive is to increase near-term R&D investment in order to take advantage of any potentially large capital cost reductions. In later periods when there is less deployed, these potentially large capital cost reductions would have less value. The high-capital cost and low-carbon characteristics of coal with CCS technology dictate that the majority of coal with CCS plants be deployed in later periods (under a carbon cap), after several periods cost reductions from learning-by-doing and learning-by-searching have passed. Under moderate uncertainty, this delay in capital deployment incentivizes lower near-term R&D investments compared to the optimal deterministic strategy, and encourages following the "wait and see" rule to take advantage of the opportunity to learn and revise decisions before making large R&D investments. Moderate near-term R&D investment is still optimal, however (as opposed to no R&D investment) because beginning to build the knowledge stock early is important in this path-dependent problem.

Overall, these results show that technology cost and performance features drive optimal capital deployment timing, and under moderate technological change uncertainty, this timing and the associated opportunity to learn and revise drives whether it is optimal to increase or decrease near-term R&D investments from the optimal deterministic strategy.

**Question 3: What role do R&D program risk profiles and specific electricity generation technology characteristics have in investment planning under uncertainty for the power sector?**

Chapters 3 and 6 discuss in detail the skewed distributions that characterize the uncertainty in R&D investment outcomes. Moreover, new empirical evidence suggests that different energy technology categories can display characteristic shapes, or risk profiles. Some technology groups such as solar power or nuclear power tend to display "high-risk, high-reward" profiles, marked by abundant opportunity for low returns to R&D investment and rare opportunity for extremely high returns to R&D investment. Other technology groups such as wind power may be marked by "slow and steady progress" profiles, with more opportunity for moderate rewards than the high-risk, high-reward group. Each of these risk profiles is also characterized by different levels of variance.

The analyses conducted in the dissertation reveal that these two characteristics of the relative risk profiles—the right-skewness of the profile, which represents high probability of low returns to R&D, and the overall risk (variance)—affect the optimal R&D investment strategy under uncertainty. First, as skewness increases, optimal R&D investment decreases from the optimal R&D investment under a symmetric uncertainty. This result generally holds across technology types and carbon scenarios. Second, as variance increases, the optimal near-term investment increases. However, the magnitude of the increase/decrease relative to no uncertainty depends on the magnitude and timing of the original optimal deterministic R&D investment (which as discussed above, is driven by the specific technologies' cost characteristics and deployment plan). In general, the more near-term R&D investment in a technology that is optimal under perfect information, the less an increase in variance will lead to a further increase in optimal R&D under uncertainty.

This is seen in the example of optimal coal with CCS versus wind technology R&D under different R&D program risk profiles. Under a carbon cap, near-term coal with CCS R&D remains relatively modest. As described above, this is because of its high initial capital costs and "wait and see" incentive in the sequential decision making framework. However, this modest near-term R&D investment encourages aggressive increases in R&D as the variance (more opportunity for higher returns) increases. The opposite is seen for optimal R&D investment in technologies such as wind power, which due to its low-cost and upfront capital deployment already sees more aggressive near-term R&D spending. In general, this large upfront R&D investment reduces the overall sensitivity to increasing variance in R&D returns.

### *8.1.2 Academic and Practical Contributions*

A central question in the current climate policy debate is how to balance near-term emission reductions through capacity deployment and future emissions reductions through investments in R&D for alternative energy technologies. The results of this study can provide valuable intuition, and a modeling approach for others to apply to study similar policy questions. The framework can easily extend to studying balanced policies for many other electricity-sector pollutants, too. Also, by developing the improvements on a simple research-scale model first, the structure is transparent and thus easier to transfer and adapt to other domains.

Academically, the research contributes to the public policy and power systems research communities by producing a new framework for studying adaptive power sector emission reduction strategies under technological change uncertainty, and for integrating with other active areas of electricity planning research. It also contributes to the developing engineering systems research community by documenting the value of a system-level view of the interactions between policy, innovation, and the power sector, and integrating three previously distinct disciplines (electricity generation expansion planning, technological change economics, and decision and uncertainty analysis) to study a complex, large-scale problem that was previously intractable. It also informs an emerging approximate dynamic programming research community by applying the method to a new, large scale problem. Finally, this research contributes to the technological change branch of economics by transparently presenting one of the first applications of including electricity sector dynamics and learning-by-searching technological change into a formal model for making investment decisions under uncertain technological change.

## 8.2 Implications for Policy

Quantitative energy and climate policy modeling has been used as a pathway to inform government and industry policy decisions for the electric power sector for many decades. Early planning models were used to aid individual utilities in developing low-cost generation capacity expansion strategies, making decisions about new utility connections, and operating their existing facilities optimally. As the U.S. electric power industry grew and became more physically connected, regional and national-level planning was informed by quantitative models that could answer questions about power flow, electricity coverage across large expanses of land, and optimal new generator locations. In the wake of electricity market deregulation in portions of the country, quantitative models began to help regulatory agencies understand the implications of the different market rules they were setting. The models also helped individual utilities gauge the profitability of potential generation and sales decisions. Finally, with respect to the natural environment and overall sustainability goals, quantitative decision support models have influenced some of the most widespread environmental laws in the country, including the U.S. Clean Air Act and Clean Air Act Amendments of 1990, and the more recent sulfur dioxide and U.S. Acid Rain rule, both affecting virtually every major electric generation facility in the country.

As discussed in Chapter 2, at present the energy and climate policy modeling community finds itself with the large task of helping federal government policy makers and other stakeholders at all levels understand the environmental and cost implications of potential future national carbon dioxide emissions reduction policies (i.e., climate policy). Many of these modeling efforts are geared towards informing policy makers about economy-wide (e.g., welfare) impacts of implementing general types of climate policies as well as specific government proposed climate policies. One recent example of such an effort is the quantitative economic modeling that was performed to assess the economic implications of the 2009 American Clean Energy and Security Act (ACES) (and its multiple predecessors in the years immediately prior). A variety of academic institutions, government agencies, trade and industry groups, consulting firms, and non-government organizations performed modeling analyses (or contracted with others to perform analyses on their behalf), and the results were used in directly shaping the language of the legislation. Other modeling analyses study questions specific to an energy sector such as how a specific sector might respond to a prescribed economy-wide climate policy, or how a policy might be optimally designed to meet the needs (e.g., emission reduction goals, reliability, etc.) of a specific sector.

Discussed throughout this dissertation, one of the great challenges to such energy and climate policy modeling efforts is the matching of quantitative models to the real-world decision making process. Current modeling tools for planning within the energy and electric power sectors are not structured to match the manner in which policy makers and other stakeholders actually make decisions. Due to numerous uncertainties, decisions about long-term problems such as how best to develop the electric power sector to manage climate concerns need to be made at different time intervals, between which additional information about the state of the world (e.g., actual technology evolution, current exogenous policies) and outcomes of past decisions are collected and assessed.

At the same time, authorities charged with making decisions about how to best allocate limited financial resources across specific technology R&D areas are calling for a need to consider uncertainty in their decision making and are beginning to outline plans for doing so. For example, in September 2011, the U.S. Department of Energy outlined its new plans for a portfolio approach for energy and electricity R&D investments. A guiding principle the agency plans to use in developing its portfolio is to hedge against uncertain outcomes of currently assumed and "reasonably assured" technology pathways with "higher-risk transformational work," (DOE, 2011). However, quantitative tools for allocating R&D between these pathways either do not exist, or are computationally intractable at the scale and structure needed.

This dissertation presents a new method that can quantitatively evaluate R&D investment portfolio designs under uncertainty. The purpose of the dissertation is not to resolve each detail required to assign specific dollar values to different partitions of the portfolio, but to illustrate the method on a stylized example. With appropriate data, the models could be scaled up to provide a quantitative decision support tool for the type of policy context described by DOE above. Rigorous calibration of all parameters to the latest empirical energy and technological change data available, inclusion of additional generation technologies and demand-side dynamics, and many other features are necessary to develop the modeling framework presented in this dissertation into an industrial-scale model useful for directly informing government or industry about specific magnitudes for the decisions they should make.

Additionally, it is worth noting that the "optimal" investment strategy revealed through such numerical models may not reflect the optimal strategy that should be followed when the full range of institutional and operational constraints of the larger "electricity and innovations systems nexus" are considered. Issues such as changes in government agency funding, extraordinary opportunities for specific technology collaborations, and stakeholder support or opposition for specific decisions can create an array of implementation and administrative contexts that must be addressed. While quantitative tools like the model presented here are a valuable mechanism for informing policy making, they are but one of many inputs to a wider deliberative process.

Still, the quantitative modeling framework is built, and the overall insights gained from the analyses performed with the new tool help by 1) providing awareness about the features needed to scale the model up for real-world decision support, and 2) informing decision makers charged with strategic R&D portfolio planning for the electricity generation sector about some general actions to either seek out or avoid—as part of an overall policy making process. For example, if institutional or other barriers to deployment of a specific technology group are anticipated, and thus deployment delayed, it may be wise to invest in R&D for that technology more modestly in the near-term and learn about interim technological change before investing more heavily. As another example, if two comparable technology groups (in terms of cost structures, deployment capability, etc.) are being assessed for R&D funding allocation and one is thought to follow a more "high risk-high reward" profile, results shown here suggest that it can be beneficial to invest more slowly in the near-term in the riskier technology. Overall, results reveal that under uncertainty, the decision to invest in R&D is not a simple "more or less" decision. Instead, the decision is highly influenced by the question of *when* a particular technology might be needed in order to achieve specific objectives (e.g., emission reductions).

## 8.3. Limitations of the New Modeling Framework

The new modeling framework presented in this dissertation brings together three established, but relatively separate fields of research—electric power systems modeling, the economics of technological change, and decision analysis. Within each of these areas, research has steadily progressed through empirical inquiry, methodological inquiry, or both. However, to keep the new modeling framework presented here computationally tractable and sensible for development and testing, several details that could otherwise make the model more useful as an applied, industrial-scale numerical model have been purposefully left out. This section presents a non-exhaustive list of some of these decisions within each of the three research areas identified above, and thus reviews limitations of the current modeling framework. Section 8.4 directly reflects upon many of these limitations, outlining future research opportunities.

### *8.3.1 U.S. National-Level Electric Power Systems Modeling*

As discussed in Chapter 4, the new modeling framework operationalizes electricity generation sector "technological change" as a reduction in the capital investment costs of new power plants. This method is utilized due to 1) the prevalence of this operationalization in the technological change empirical and modeling literatures, 2) data limitations in operationalizing it using other means, and 3) a need to choose *a* pathway to incorporate technological change for the purposes of model development. However, as Chapter 2 mentions, there are many pathways for technological change to affect electricity generation sector planning.

On the "supply side" of the electricity generation expansion planning problem, advances in technology through basic science and applied R&D can also affect technical performance characteristics of power plants, such as reduction in operating heat rates (i.e., the efficiency with which primary fuel-based energy is converted into electrical energy) or increase in the efficiency with which pollutant emissions are captured, both of which would decrease the variable and operational costs of generating electricity as well. Additional pathways for total cost reduction have not been incorporated in the current version of the model.

Also excluded from the model are the numerous technology advances occurring on the demand side of the electricity generation expansion planning "equation." A key objective of expansion planning is to build adequate electricity generation infrastructure in order to reliably meet future electricity demand. However, numerous efforts to improve the efficiency with which electricity is consumed (e.g., energy-efficient residential appliances) and the time of day it is consumed (e.g., time of day pricing, commercial and residential contracts for regulating electricity time of use, "smart grid" development) will affect the amount of electricity demanded during a given day or year, and thus the amount of generation infrastructure to build. Additionally, a large shift towards plug-in electric vehicles in the transportation sector will increase the amount of electricity demanded, potentially requiring additional infrastructure to support the increased demand (Short & Denholm, 2006). On the other hand, successful innovation in fuel cells and other emerging technologies to introduce large-scale storage on the electricity grid can have the opposite effect and potentially decrease the amount of new generating infrastructure or types of technologies needing to be built (Sullivan, Short & Blair, 2008). Each of these technology areas—demand energy efficiency, plug-in electric vehicles, and electricity storage (among others)—are actively involved in the innovation process, and will thus affect the design of optimal electricity R&D and capital investments under uncertainty. Future versions of the framework presented here should include such demand-side innovation efforts.

Lastly, there are many emerging technology areas that are excluded from this initial modeling framework that will help the framework scale for industrial-scale application. The U.S. electric power generation sector is represented using ten technology categories and their respective cost structures and performance characteristics (the stochastic modeling framework reduces this to five). However, industrial scale national-level applications typically use a minimum of twenty different categories to represent additional emerging technologies (e.g., offshore wind, ocean wave technology), and disaggregate existing technologies to better represent their different costs and characteristics (e.g., conventional pulverized coal plants, supercritical pulverized coal plants, integrated gasification combined cycle coal plants). Scaling the model to include these additional technologies is a relatively straightforward process, although outside the scope of this dissertation.

The second key limitation in using the current model for decision support in government R&D investment planning is the lack of representation of the heterogeneous nature of the U.S. electricity generation market. The current modeling framework uses a centralized approach to capacity expansion, making the assumption that 1) a hypothetical central planner is charged with making operation and new capacity addition decisions for the entire U.S. electricity generation system, or 2) the system operates under perfect competition. While such an assumption can be appropriate for the long-term strategic nature of the current research, it does not represent the true nature of the underlying system. Currently, about half of the U.S. operates under a market-based structure and individual companies make decisions about their new capacity investments. Resolving such details using a decentralized planning approach could reveal additional insights and be useful for national-level policy setting (e.g., Kilanc & Or, 2008).

### *8.3.2 Representing Technological Change*

Limitations in the modeling framework with respect to representing the dynamics of technological change stem from the aggregation of public and private R&D pathways in the model, the types of technological change excluded in the model, and the challenges inherent in integrating results from innovative empirical research into quantitative numerical models for energy and climate policy.

One of the key limitations in the new modeling framework is its inability to distinguish between public and private innovation processes. In the current model, public and private R&D is represented as a lumped entity, which performs R&D activities for electricity generation technologies. This decision was made in order to build as simple a model as possible to begin developing the numerical framework, but as Chapter 2 discusses, much of the R&D effort for electricity generation technologies takes place in the private sector. As private entities face different incentives for pursuing R&D

activities than public entities, disaggregating the model's R&D sector may reveal more information about the effect of technological change on the optimal total R&D investment strategy. For example, due to the lack of differentiation between public and private R&D activity, the response of "upstream" private manufacturers to increased "downstream" demand through new capacity additions is not adequately represented. Likewise, the public and private sector tend to play different roles in the innovation process—with public R&D targeted more towards advances in basic science and private R&D more towards applied activities and commercialization (Deutch, 2005). The current model treats all R&D used for an aggregated "technological change."

Next, there are several pathways for technological change in the energy sector, only some of which are explicitly captured in the current model. The current model applies only learning-by-doing (LBD) and learning-by-searching (LBS) for emerging technology categories in order to construct and demonstrate use of the numerical platform. However, other important sources for technological change include knowledge spillovers from innovative activity occurring for other technologies within the same industry, or even outside the industry. It can also include a general background (economy-wide) rate of technological change that simultaneously affects all technologies. Implicit in the current model is the assumption that all other technological change is captured through the LBD and LBS pathways, but a fairer representation would explicitly account for it.

Finally, there is a general lack of empirical data and analysis available to directly calibrate the multiple learning parameters used in the dissertation model, and this creates a limitation. Historical two-factor learning rates for emerging technologies such as coal with CCS technology are not yet available, due to its relatively new use in the electricity generation sector. Most learning rates that are available are based on demonstration projects or from its use in enhanced oil recovery applications. As mentioned in Chapter 3, private R&D data is not publicly available for econometric analysis (or other purposes) and therefore integration into numerical models is not straightforward. Empirical research that has been performed to estimate rates for technological change via other means such as patent data or expert elicitation pose other challenges (e.g., interpretation, calibration) for integrating into technology-specific partial equilibrium models. Thus, the technological change module used in the current model represents a springboard for testing several alternative learning rates and pathways of technological change, as well as for rigorous more rigorous calibration to results from empirical data studies.

### *8.3.3 Decision Making under Uncertainty Modeling*

There are two main limitations in the dissertation's methods with respect to their ability to make decisions under uncertainty; both concern the type of uncertainties able to be considered. First, a key uncertainty in the electricity and innovations systems nexus studied in this dissertation is the amount of cumulative emissions reduction required from the generation sector. This is directly related to the notion that there is great uncertainty in the earth system response to rising carbon dioxide levels, and uncertainty about what types of future climate policies will be implemented to tackle emissions reduction goals. Unfortunately, the current version of the model lacks the ability to study optimal investment strategies under uncertain carbon caps because the pathway for making decisions about additional generating capacity is not yet active in the stochastic model.

Sensitivity analysis in Chapter 5 provides some initial intuition about the behavior of the optimal R&D and capital investment strategy under varying carbon targets, but this does not formally integrate uncertainty and the opportunity to learn and revise investment decisions between periods. Activating the generation capacity investment decisions within the stochastic model is a non-trivial task, requiring additional methodological work in the field of operations research.

The second key limitation in the structure of the decision under uncertainty model presented in the dissertation, and often inherent in the nature of quantitative modeling of socio-technical systems, is the lack of decision support for certain unforeseeable uncertainties. A review of key uncertainties that electricity and energy system modelers often consider in their quantitative models is provided in Chapter 2. However, a separate category of uncertainties exists that describe "game-changing" activities—currently unimaginable events, with little data to support their integration into quantitative models, and for which the probability of their occurrence is unknown. With respect to new technologies to help reduce or eliminate carbon dioxide emissions from the electric power sector, such revolutionary technologies may be unintended consequences from otherwise dedicated R&D activities, or from entirely new pathways. A limitation of the modeling framework presented here is that it does not have a strong ability to explicitly capture the effects of such uncertain technological change. In the current model, integration of technological change uncertainty necessarily requires upfront assumptions about the initial costs and performance characteristics for technologies included in the model, and doing so would essentially place the hypothetical technology into one of the already existing technology groups. An interesting global energy model that attempts something similar does so by integrating nuclear fusion technology into their technology suite, but necessarily chooses a technology "type" to assign to its game-changer (Lechon et al., 2005). One method of implicitly accounting for such uncertainties involves considering what the impact of the game changing technology would be in the system (e.g., dramatically reduced electricity demand, unlimited free fossil fuels) and incorporating uncertainty in that variable or parameter. However, overall this limitation encourages the use of separate, simultaneous decision support tools aimed more towards managing these types of uncertainties such as more formal, qualitative scenario planning techniques.

## 8.4. Future Work

There are a number of significant extensions to this dissertation work that can better capture important details within the U.S. electric power sector, represent technological change, and design an even more efficient algorithm for exploring optimal investment decisions under uncertainty.

First, while the dissertation model uses the United States as a case, and purposely incorporates only the minimum constraints representing the physical electricity system due to a focus on developing the modeling framework, there are several layers of detail that can improve the results. Four immediate opportunities for research include: 1) separating public and private R&D by including opportunity cost constraints across R&D efforts and defining a profit-maximizing private R&D sector (currently, the model considers a single R&D sector and thus the socially optimal level of R&D); 2) disaggregating electricity demand balancing areas to formally represent the spatially heterogeneous nature of U.S. electricity supply and demand; 3) transforming the underlying (currently centralized) capacity planning model to consider the competition that defines much of the actual U.S. electric power generation sector; and 4) extending the current model to include energy efficiency and demand-side technological change, distributed generation technologies (e.g., electric vehicles), and additional pathways for technology-based cost reduction (e.g., through increased power plant efficiencies).

There are also two main immediate opportunities for research on the ADP stochastic decision model. First, investigating alternative "explore-exploit" sampling strategies for reducing the search space when solving for the optimal policy will further increase the speed and precision of the model. Currently, a single run of the model uses approximately 3-4 minutes of CPU time, and this can be reduced further with alternative sampling strategies. Increasing the efficiency with which the algorithm solves will also be useful for the second research opportunity, which will greatly increase dimensionality: activating the new capacity decisions within the stochastic model. Doing so will require utilizing alternate techniques for value function approximation instead of the method applied in the current model, but will ultimately allow for several additional types of inquiry.

Finally, results from this research illuminate the need for additional empirical study on technological change within specific electricity sector technology categories. The majority of current research in gathering and analyzing data to study technological change within the energy sector remains too aggregated to be integrated into technology-specific engineering-cost models such as the model developed here. For the purposes of model development and illustration, aggregated data was utilized in this dissertation, but future versions can consider calibrating to more specific technology types if and when the data become available. Furthermore, additional empirical study linking inputs to public and private innovation (separately) to outcomes, and characterizing the uncertainty underlying these outcomes, would be extremely useful for the electricity systems modeling community to begin scaling up decision under uncertainty modeling frameworks such as the one introduced in this dissertation for practical policy making.

# Appendix A Full Formulation of the Electricity Generation Capital and R&D Investment Planning Model

*Indices and exogenous parameters*

| | |
|---|---|
| $t$ | period |
| $g$ | generation technology category |
| $g^*$ | dispatchable technology categories |
| $g^{**}$ | non-dispatchable technology categories |
| $g^{***}$ | no new build technology categories |
| $g^{****}$ | emerging (learning) technologies |
| $d$ | demand slice |
| $r$ | annual discount rate |
| $fix\_om\_rate_g$ | fixed O&M cost for technology g |
| $duration_d$ | length (in hours) for demand slice d |
| $fuel\_cost_{t,g}$ | fuel cost for technology g in period t |
| $fuel\_growth\_rate_g$ | annual fuel cost growth rate for technology g |
| $var\_om\_rate_g$ | variable O&M cost for technology g |
| $hebscale_g$ | knowledge stock scaling parameter for technology g |
| $retire\_rate_g$ | per period retirement rate for technology g |
| $CAPC_{0,g}$ | initial capital cost for technology g |
| $\eta 1_g$ | learning-by-doing elasticity for technology g |
| $\eta 2_g$ | learning-by-searching elasticity for technology g |
| $\alpha_g$, $\beta_g$, $\phi_g$ | innovation possibilities frontier parameters for technology g |
| $\delta_g$ | per period knowledge stock discount rate for technology g |
| $demand_d$ | power level (gigawatts) for demand slice d |
| $emission\_rate_g$ | carbon emission rate for technology g |
| $ecap$ | cumulative carbon emissions cap |
| $availability\_rate_g$ | availability rate (including maintenance & outages) for technology g |
| $demand\_peak$ | power level (gigawatts) for peak demand slice |
| $k$ | annual demand growth rate |
| $reserve\_margin$ | reserve margin (%) for electricity reliability |
| $initial\_capacity_g$ | initial installed capacity for technology g |
| $install\_uprate_{g^{****}}$ | maximum installed capacity rate of change between periods for emerging technologies |

*Exogenous variables*

| | |
|---|---|
| $RR_t$ | accumulated social discount factor in time t |
| $KK_t$ | accumulated demand growth factor in time t |
| $FP_{t,g}$ | accumulated fuel cost growth factor in time t for technology g |

*Endogenous variables*

| | |
|---|---|
| $REBACK_{t,g}$ | R&D investment for technology g in period t |
| $NEW\_CAPACITY_{t,g}$ | new capital installations for technology g in period t |
| $FC_t$ | total fixed costs in period t |
| $VC_{t,g}$ | variable costs for technology g in period t |
| $TOTAL\_CAPC_{t,g}$ | capital investment costs for technology g in period t |
| $TOTAL\_FIX\_OM_{t,g}$ | total fixed O&M costs for technology g in period t |
| $PWROUT_{t,d,g}$ | total electricity generation for technology g in demand slice d in |
| $E_t$ | total emissions in period t |
| $CAPC_{t,g}$ | capital cost for technology g in time period t |
| $NEWHEB_{t,g}$ | new human knowledge for technology g in period t |
| $HEBACK_{t,g}$ | human knowledge stock for technology g in period t |
| $NETLOAD_{t,d}$ | net electricity demand (total demand less non-dispatchable generation technologies) in demand slice d in period t |

*Objective*

$$\min_{NEW\_CAPACITY_{t,g}, REBACK_{t,g}} NPV \tag{1}$$

*Objective Function Equations*

$$RR_t = (1+r)^{-5(t-1)}$$

$$NPV = \sum_{g,t}^{G,T}\left[FC_{t,g} + VC_{t,g} + REBACK_{t,g}\right] * RR_t \tag{2}$$

$$FC_t = \sum_g^G TOTAL\_CAPC_{t,g} + \sum_g^G TOTAL\_FIX\_OM_{t,g} \tag{3}$$

$$TOTAL\_FIX\_OM_{t,g} = 5\, CAPACITY_{t,g} fix\_om\_rate_g \qquad \text{(fixed costs per period)} \tag{4}$$

$$FP_{t,g} = \left[1 + \left(\frac{fuel\_growth\_rate_g}{100}\right)\right]^{5(t-1)}$$

$$VC_{t,g} = 5\sum_{d}^{D} PWROUT_{t,d,g}\, duration_d \left(fuel\_cost_{t,g} FP_{t,g} + var\_om\_rate_g\right)$$
(variable costs per period) (5)

$$TOTAL\_CAPC_{t,g} = CAPC_{t,g} NEW\_CAPACITY_{t,g}\, hebscale_{t,g} \tag{6}$$

$$NEW\_CAPACITY_{t,g} = CAPACITY_{t,g} - \left[CAPACITY_{t-1,g}\left(1 - retire\_rate_g\right)\right] \tag{7}$$

$$CAPC_{t,g} = \frac{CAPC_{0,g}}{(CAPACITY_{t,g}^{\eta 1g})(HEBACK_{t,g}^{\eta 2g})}$$
(2-factor learning curve) (8)

$$NEWHEB_{t,g} = \alpha_g \frac{1}{5} REBACK_{t,g}^{\beta} HEBACK_{t,g}^{\phi}$$
(annual innovation possibilities frontier) (9)

$$HEBACK_{t+1,g} = 5\, NEWHEB_{t,g} + \left(1 - \delta_g\right) HEBACK_{t,g}$$
(knowledge stock accumulation) (10)

$$E_t = 5\sum_{d,g}^{D,G} emission\_rate_g PWROUT_{t,d,g} duration_d$$
(emissions per period) (11)

*Constraints*

$$\sum_{t}^{T} E_t \leq ecap$$
(cumulative emissions cap) (12)

$$\sum_{g^*}^{G^*} PWROUT_{t,d,g^*} = NETLOAD_{t,d}$$
(electricity demand balance) (13)

$$KK_t = (1 + k)^{5(t-1)}$$

$$NETLOAD_{t,d} = demand_d KK_t - PWROUT_{t,d,g^{**}} \tag{14}$$

$$PWROUT_{t,d,g} \leq CAPACITY_{t,g} \tag{15}$$

$$\sum_{d}^{D} PWROUT_{t,d,g} duration_d \leq CAPACITY_{t,g} * 8760 * availability\_rate_g \tag{16}$$

$$\sum_d^D PWROUT_{t,d,g**} = CAPACITY_{t,g**} availability\_rate_{g**} \tag{17}$$

$$\sum_g^G CAPACITY_{t,g} \geq demand\_peak \times KK_t(1 + reserve\_margin)$$

(reliability requirement) (18)

$$CAPACITY_{1,g} = initial\_capacity_g$$

(starting with the existing system) (19)

$$CAPACITY_{t+1,g****} \leq install\_uprate_{g****} \times CAPACITY_{t,g****}$$

(maximum rate of change for installed capacities) (20)

$$NEW\_CAPACITY_{t,g***} = 0$$

(no new builds) (21)

# Appendix B Innovation Possibilities Frontier Calibration

The purpose of this appendix is to detail the method for calibrating the innovation possibilities frontier (IPF) parameters used in the new modeling framework to established data in the literature. The IPF corresponds to Equation 9 in the full model described in Appendix A, and provided again below.

$$NEWHEB_{t,g} = \alpha_g REBACK_{t,g}^{\beta} HEBACK_{t,g}^{\phi} \qquad \text{(annual innovation possibilities frontier)} \quad (9)$$

As described in the Chapter 3 literature review and in the presentation of the deterministic modeling framework in Chapter 5, previous relevant numerical models for decision making in the energy and environment realm use a single variable to represent the dynamics that produce new knowledge. These models typically assume that new knowledge is a direct function of the dollars invested into R&D for a specific technology, often a one-to-one relationship. They then assume that the total knowledge stock for a specific technology grows as a function of this new knowledge, although often accounting for depreciation of the existing knowledge stock. Such a framework resembles the following:

$$HEBACK_{t+1,g} = REBACK_{t,g} + (1 - \delta_g) HEBACK_{t,g}$$

where $HEBACK_{t,g}$ is the knowledge stock at time, $t$, for technology, $g$, $REBACK_{t,g}$ is the amount invested into a research and development program at time, $t$, for technology, $g$, and $\delta_g$ is a technology-specific per-period depreciation rate for the knowledge stock for technology, $g$.

The modeling framework used in this dissertation seeks to unpack the mechanism by which knowledge stock accumulates over time and new knowledge is created. New knowledge creation occurs via the IPF shown in Equation 9 above—as a function of both the level of R&D investment in a specific technology and the current level of the cumulative knowledge stock. The knowledge stock then accumulates as a function of this new knowledge:

$$HEBACK_{t+1,g} = NEWHEB_{t,g} + \left(1 - \delta_g\right)HEBACK_{t,g} \tag{10}$$

Using this framework requires finding suitable parameters α, β, and ϕ for each technology for the IPF. While detailed empirical calibration of IPF parameters to new or improved data is beyond the scope of this dissertation, there was interest in being able to study the behaviors of both R&D investment efficiency and knowledge stock efficiency individually. Additionally, there is general interest in the energy decision modeling and endogenous technological change community to explore alternative forms for incorporating learning dynamics into numerical models (Clarke et al., 2004); this dissertation partially seeks to contribute to that discussion.

## Method

The innovation possibilities frontier for each emerging technology (coal with CCS, nuclear, wind, and solar) is calibrated to retain the final capital cost reduction amounts expected from published two-factor learning-by-searching rates in the literature. Overall, the role of the innovation possibilities frontier is to create new knowledge (Equation 9), which feeds into a cumulative technology-specific knowledge stock (Equation 10) used to reduce capital costs through the following two-factor learning curve (Equation 8 in Appendix A),

$$CAPC_{t,g} = \frac{CAPC_{0,g}}{(CAPACITY_{t,g}^{\eta 1g})(HEBACK_{t,g}^{\eta 2g})} \qquad \text{(2-factor learning curve) (8)}$$

where $CAPC_{t,g}$ is the capital cost of technology $g$ in time period $t$, $CAPC_{0,g}$ is the initial capital cost, $CAPACITY_{t,g}$ is the total installed capacity of technology $g$ in time period $t$, $HEBACK_{t,g}$ is the knowledge stock for technology $g$ in time period $t$, and $\eta 1_g$ and $\eta 2_g$ are the learning-by-doing and learning-by-research elasticities for technology $g$, respectively.

The goal of the calibration is to achieve as closely as possible, the amount of capital cost reduction expected through the learning-by-searching pathway for each technology based on published two-factor learning-by-searching rates (LSR), but instead using the full IPF-mechanism for the underlying growth of $HEBACK_{t,g}$. (The learning-by-doing (LBD) pathway is not changed, and published two-factor LBD rates are used.) Using published two-factor LSR and learning-by-doing rates (LDR), a trajectory for capital cost $(CAPC_{t,g})$ as a function of knowledge stock ($HEBACK_{t,g}$) and cumulative installed capacity ($CAPACITY_{t,g}$ ) is first computed. Both knowledge stocks and cumulative capacity are initialized to 1.0 and for simplicity, double every period. The calibration for the IPF then aims to grow a knowledge stock that results in the same rate of capital cost reduction as the original learning-by-searching rate (LSR); the rate of capital stock growth remains at 100% per period.

Published LSRs and LDRs in Barreto and Kypreos (2004) are used for the calibration. These rates describe the cost reduction that occurs from a doubling of the knowledge stock, and follows directly from the traditional experience curve "progress ratio" concept (Ibenholt, 2002).

$$LDR = 1 - 2^{\eta 1},$$

$$LSR = 1 - 2^{\eta 2},$$

where the parameters $\eta 1$ *and* $\eta 2$ are technology specific. Table B-1 provides the rates used to develop the capital cost trajectory of the original (target) cost reduction curve, and the corresponding learning indices ($\eta 1$ *and* $\eta 2$) used for the two-factor learning-curve in the dissertation model.

**Table B-1 Learning-by-Searching Rates and Indices by Technology Category**

| Technology | LSR | Corresponding LDR Index ($\eta 1$) | LSR | Corresponding LSR Index ($\eta 2$) |
|---|---|---|---|---|
| Coal with CCS* | 0.04 | 0.05889 | 0.02 | 0.02915 |
| Nuclear | 0.04 | 0.05889 | 0.02 | 0.02915 |
| Wind | 0.16 | 0.25154 | 0.07 | 0.10470 |
| Solar | 0.25 | 0.41504 | 0.10 | 0.15200 |

Source: Barreto and Kypreos (2004).
* Coal with CCS technology is assumed to learn at the same rate as nuclear power technology in this dissertation.

Next, to calibrate the IPF for each technology, new knowledge created needed to accumulate into a knowledge stock that allowed capital costs to decline at the same rate as the target curve when used in the two-factor learning-curve formulation (Equation 8) with the LSR and LDR indices from Table B-1. To do so, existing values from the literature for two of the three IPF parameters were applied (Popp, 2006), and the third parameter was solved for using a least-squares minimization method. The parameters for $\beta$ (elasticity of new knowledge with respect to R&D investment) and $\phi$ (elasticity of new knowledge with respect to knowledge stock) in the published literature are for a single lumped energy technology group, so they are held constant across the four technologies here. Following Popp (2004), $\beta = 0.10$ and $\phi = 0.54$. Finally, to compute capital cost reductions through the IPF, levels for knowledge stock, capital stock, and R&D investment for each technology are needed. All knowledge stocks are initialized at 1.0 in the model. Therefore, an initial value of 1.0 is used, and all subsequent values for the knowledge stock are a result of applying the knowledge stock accumulation in Equation 10 above, with a corresponding annual depreciation rate of 0.01. Capital stocks grow at an exogenous rate of 100% per period, in line with the method used for the target curve. Following Barreto and Kypreos (2004), values applied for annual R&D investment are given in Table B-2.

**Table B-2 Annual R&D Investment by Technology (in Million USD)**

| Technology | Annual Total R&D Investment |
|---|---|
| Coal with CCS** | 773 |
| Nuclear | 773 |
| Wind | 409 |
| Solar | 409 |

Source: Barreto and Kypreos (2004).
* Values in Barreto and Kypreos are given in 1998 dollars; for the purposes of calibration this is retained.
** Coal with CCS technology is assumed to have the same level of investment as nuclear for the purposes of calibration.

For each technology IPF, these values for R&D investment, capital stock, initial knowledge stock, parameters $\beta = 0.10$ and $\phi = 0.54$, a knowledge stock depreciation rate of 1%, and a target capital cost trajectory from the original published LSR and LDRs, combined with Equations 8, 9, and 10, are used to determine an optimal value for the scalar $\alpha$ in the IPF through a simple least-squares minimization technique. Results from this optimization are shown in the figures below, depicting both the original target capital cost curve for each technology, and the final curve after the IPF calibration. Final values for $\alpha$ are given in Table B-3.

**Table B-3 Calibrated IPF Parameter Values for Deterministic Reference Model**

| Technology | IPF $\alpha$ | IPF $\beta$ | IPF $\phi$ |
|---|---|---|---|
| Coal with CCS** | 0.3910 | 0.1 | 0.54 |
| Nuclear | 0.3910 | 0.1 | 0.54 |
| Wind | 0.4389 | 0.1 | 0.54 |
| Solar | 0.4539 | 0.1 | 0.54 |

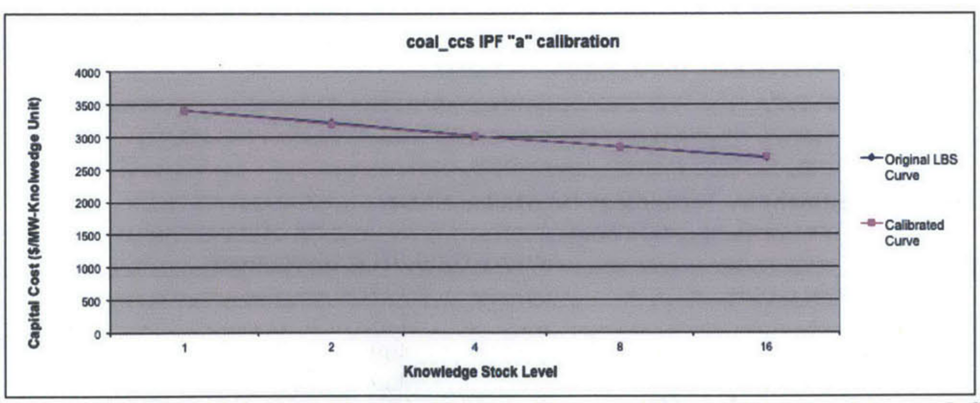


**Figure B-1 Original capital cost trajectory for coal with CCS technology and final capital cost trajectory for coal with CCS technology after IPF calibration**

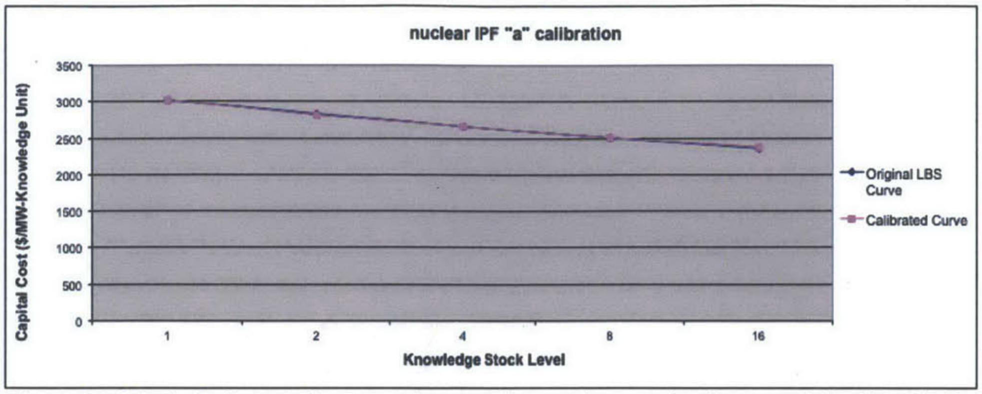


**Figure B-2 Original capital cost trajectory for nuclear technology and final capital cost trajectory for nuclear technology after IPF calibration**

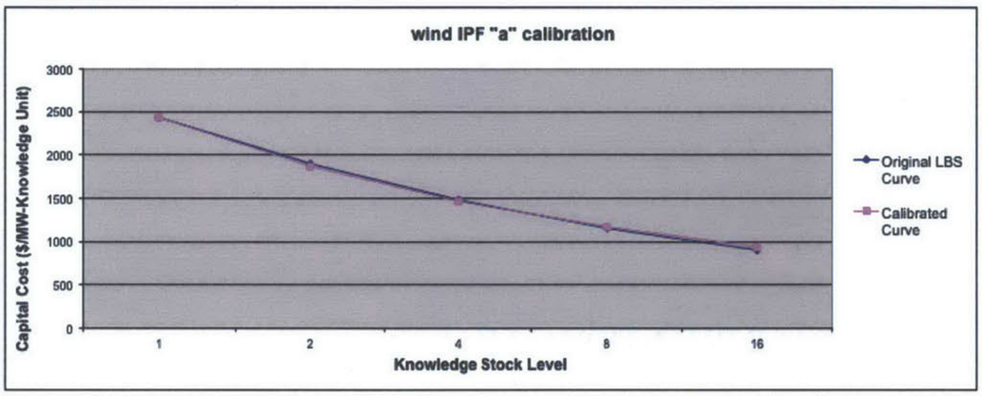


**Figure B-3 Original capital cost trajectory for wind technology and final capital cost trajectory for wind technology after IPF calibration**

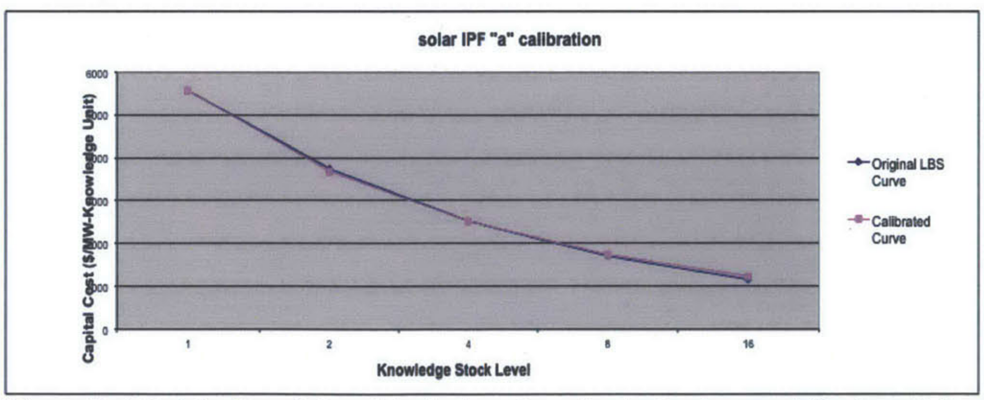


**Figure B-4 Original capital cost trajectory for solar technology and final capital cost trajectory for solar technology after IPF calibration**

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# Appendix C The Case for Representing Electricity System Dynamics in Energy Decision Models

The following appendix motivates the need to represent a minimum degree of realism of the unique dynamics of the power system when studying electricity sector investment decisions and emissions reduction potentials. As discussed in the Chapter 3 literature review, many interactions are often missed in economic models that assume fixed operations and various exogenous trajectories to study electricity investment planning and related emissions. Also, as explained in Chapter 4.4, there are a wide range of constraints and dynamics involved in how the physical electric power system operates which make the operations and investment planning problem so distinct.

This appendix presents results from a brief numerical experiment where two key constraints in the optimization problem are relaxed in order to simulate removing the representation of two important dynamics in the current modeling framework. The constraints chosen for removal aim to simulate the relatively rudimentary level at which electricity system operations are commonly represented in many well-known economic models in use today for energy sector investment planning and policy analysis.

The first constraint relaxed for the simulation involves removing the net-load approach used for the energy demand balance requirement. As described in Chapter 4.4 in detail, a net-load approach is used to represent the reality that in an electric power system without effective storage capability, power generated must equal power consumed. The net-load approach requires that this equality be met after total power generated from intermittent renewable resource technologies such as solar power, as well as total power generated from highly-operationally-constrained base-loaded technologies such as nuclear power, are subtracted from the amount of electricity demand which much be met. This approach allows modeling to first-order the effects of intermittent renewable resources, and as the dominant operational constraint of nuclear power plants. It does so by assuming that when these sources are generating power, that power *is* being used to satisfy demand (rather than being otherwise shed or curtailed). Traditionally, in less sophisticated electricity operations and investment planning models, as well as in modern larger economic models used for policy analysis, these effects are ignored and it is assumed that technologies such as solar and nuclear are able to meet electricity demanded in the same manner as a natural gas plant or a coal-fired power plant—that is, they are able to be turned "on" and "off" on demand. In the relaxed version of the problem, all technologies compete equally to meet the full amount of electricity demanded.

The second change in the model allows all installed generators on the system to be available to generate at any time during the day (e.g., they are all "dispatchable" technologies). In the reference model, given its high diurnal variability, solar power is constrained to producing electricity to meet a portion of electricity demand only during peak solar incidence times, and otherwise does not produce (when the sun is not shining). In the relaxed version of the model, solar power is assumed to be dispatchable, along with all of the other technologies. In doing so however, solar power's resource availability rate is also decreased from 90% available *and* generating in only peak slices, to 30% available *to* generate during all time slices in order to continue simulating its limited resource availability rate. This use of solar power's capacity factor is in-line with how such an intermittent, temporally-constrained resource is represented in top-down or less detailed models.

Figure C-1 and Figure C-2 show the results from the reference model under business-as-usual (BAU) (no carbon cap) and from the relaxed version of the model, to simulate more rudimentary power system dynamics, respectively. As usual, R&D investment decisions and installed generating capacities are provided; per period generation by technology and per period emissions trajectories are also shown for both sets of results.

The difference in results is readily apparent. Under the relaxed constraints, solar technology R&D investment appears; this is not the case under the reference model with a minimum degree of operational realism. Additionally, this new solar R&D investment appears to offset a small fraction of wind R&D investment in all periods. Installed capacities follow this plan, with new solar technology capacity additions beginning in Period 4 (in place of a portion of the wind capacity in the reference model scenario). New (conventional) coal capacity is also added at a faster rate beginning in Period 2 under the relaxed constraints. This shift to investing in solar R&D under the relaxed constraints is not surprising given the assumption that the solar generators are able to operate at any time during the day, on demand. Under the reference model, solar power remains locked out of development due to its high initial capital cost, low resource availability, specific learning characteristics, and general lack of role under realistic carbon targets. However, under the relaxed constraints, the assumption that solar availability is much more flexible gives it an unrealistic operations capability, and thus in the context of this relaxed model, there is a false incentive for its development.

A second key difference between the two model results is in the emissions profile, and underlying generation (operation) of the system to meet demand. Under the relaxed constraints, the tendency is to be more lenient with emissions in the near-term, allowing emissions to increase before settling to a benchmark from which emissions grow unconstrained. The reason for this can be explained by the difference between the generation by technology graphs from the two results. In the reference model, nuclear power is base-loaded and therefore required to run and fill a certain percentage of demand. This simulates relatively realistic operations of nuclear power plants which are very operationally constrained and if installed, *do* tend to operate near maximum capacity most of the time. However, in the relaxed version of the model, although nuclear power is installed, it does not generate any electricity to meet demand. This is because the base-load representation of nuclear power was removed from the model and it now has to compete with other technologies to meet demand. This results in the system choosing to operate additional (or for longer) less capitally-expensive and less fuel-expensive old coal and new coal-fired plants, and some additional combined cycle natural gas-fired plants, in place of nuclear plants. As a result of these increased carbon-emitting technologies, emissions increase in the relaxed case to a higher level.

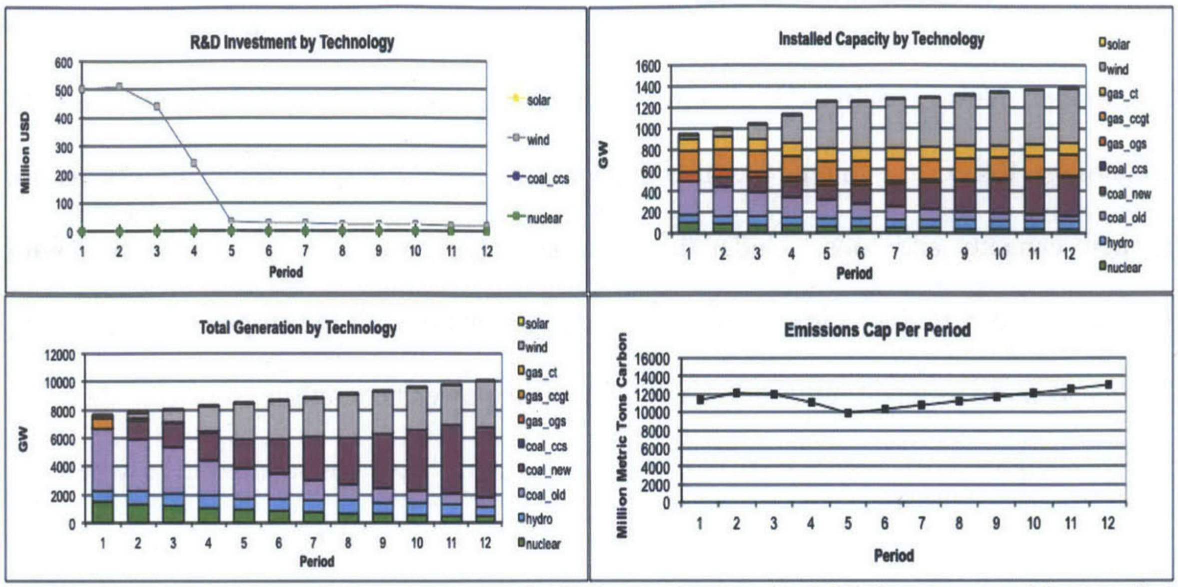


**Figure C-1 Reference model results under BAU (no carbon cap): R&D investments (a), Installed Capacities (b), Total Generation by Technology (c), and Emissions Per Period (d)**

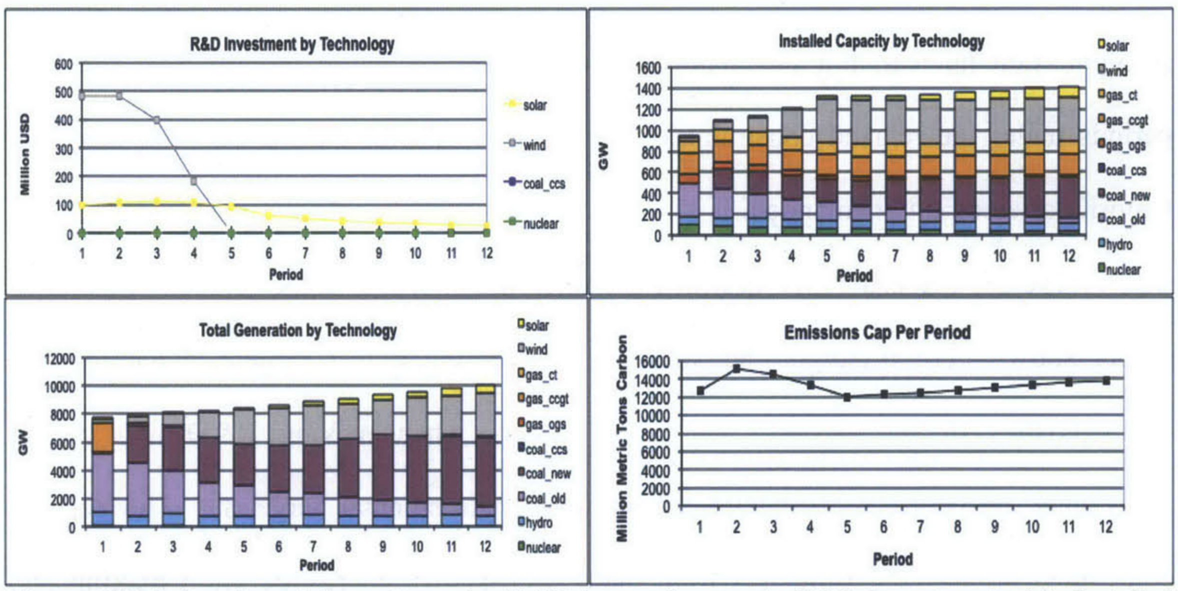


**Figure C-2 Relaxed model results under BAU (no carbon cap): R&D Investments (a), Installed Capacities (b), Total Generation by Technology (c), and Emissions Per Period (d)**

Figure C-3 and Figure C-4 additionally show the full set of results from the reference model and the relaxed model, respectively, both under a moderate (50% BAU) carbon target. The trends and differences between the two models under a moderate carbon target follow the same general pattern as those witnessed under BAU. Under the relaxed constraints, solar R&D investment is present, and reduces a fraction of wind R&D investment. New capacity additions follow this R&D investment pattern. Coal with CCS technology R&D investments are also exaggerated under the relaxed constraints, as are its new capacity additions. Under the moderate target, a focus is placed on coal with CCS technology given its low carbon emission rate, but overall the emphasis placed on it in this scenario is again due to the lack of nuclear power generation. Cheaper fuel at a lowered capital cost allows coal with CCS to become very cost-competitive when the need to run nuclear plants is not considered. An even blunter difference between the two model results is seen in per period emissions under the moderate carbon target. Near term emissions still increase due to the shift to carbon-emitting technologies instead of zero-emission nuclear, but the majority of emissions reduction is shifted to the later periods under the relaxed constraints when cheap coal with CCS plants can meet the majority of electricity demanded.

Overall, the difference between the reference model and the relaxed constraints model shown here highlight the value in considering power system dynamics and characteristics of the physical electricity system when making R&D and capital investment decisions (either with or without environmental targets). The relaxed constraints model here simulates what many well-known energy decision making and policy analysis models use to represent the power system, and as shown here, this can lead to an exaggerated focus on technologies (e.g., solar power) that may not realistically be able to contribute to the minimum objective of reliably meeting electricity demand as much as hoped. This can lead to unrealistic expectations for emerging technologies, thus wasting funds and failing to truly minimizing total system costs.

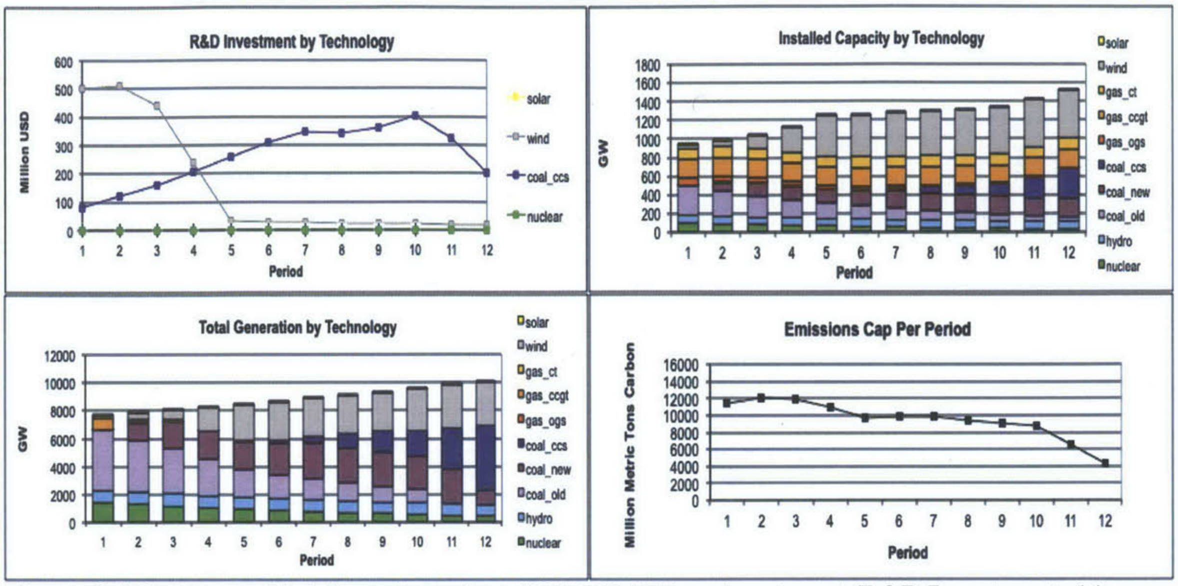


**Figure C-3 Reference Model results under a MODERATE carbon target: R&D Investments (a), Installed Capacities (b), Total Generation by Technology (c), and Emissions Per Period (d)**

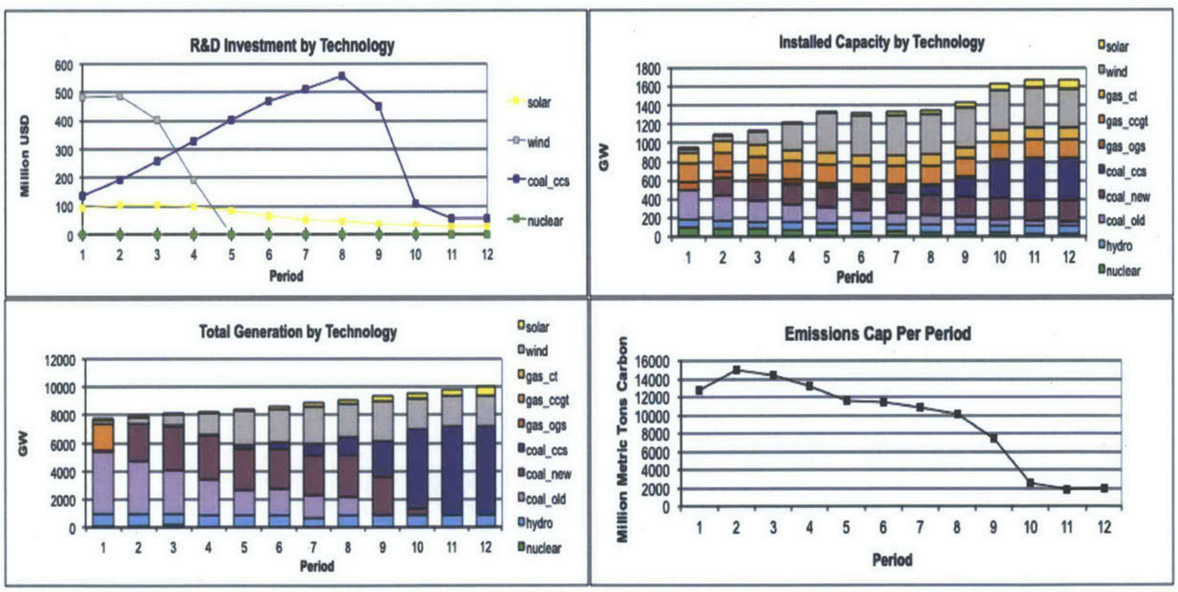


**Figure C-4 Relaxed Model results under a MODERATE carbon target: R&D Investments (a), Installed Capacities (b), Total Generation by Technology (c), and Emissions Per Period (d)**

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# Appendix D Approximate Dynamic Program Model Validation

This appendix presents results from validating the numerical models used for the stochastic analysis in Chapters 6 and 7. There are two steps in this validation. First, Chapter 6 explains that a six 10-year period, 5-technology model is used, which diverges from the more comprehensive twelve 5-period, 10-technology model used for the deterministic analyses in Chapters 4 and 5. Therefore, Part 1 of the appendix presents evidence that a new (deterministic) six-period model behaves in a qualitatively similar manner as the full-scale deterministic model, imparting confidence that it is an appropriate platform to build upon for the stochastic extension of the study. The second step is to confirm that the deterministic six-period model and a new stochastic six-period model with no uncertainty, behave similarly. Part 2 presents the results from validating the approximate dynamic program used to solve the reference stochastic problem.

### Part 1 3-Stage Model Validation

To gain confidence that the reduced 6-period, 5-technology R&D and generation capacity investment planning model is appropriate to build upon in the stochastic extension of the dissertation, it is important that the model performs in a similar manner as the original deterministic model used to gain the insights from Chapter 4 and 5. In this way, model behavior under uncertainty can be validated by sensitivity analysis results from Chapter 5, and new insights gained from the stochastic study in Chapters 6 and 7 can be more easily compared with the deterministic study. The goal of this step in the validation is that the overall patterns in R&D and new capacity investments across the different carbon target scenarios studied behave similarly.

Figure D-1 shows optimal R&D investments and installed capacities for the reduced model and the original model under the BAU carbon scenario. R&D investments in wind are witnessed in both cases, with no other R&D investments in other technologies. In terms of installed capacity, both models' electricity systems are dominated by conventional coal baseload throughout most periods, followed by a moderate amount of natural gas capacity. Both systems also see a similar "build outs" of wind power after the initial periods, when the cost of wind technology decreases sufficiently from learning. Coal with CCS technology capacity—the fifth technology available—is not seen in the reduced model or in the original model where it is available from the larger suite. Finally, nuclear and hydropower is not seen in the reduced model because they are not available in the suite of technologies to choose from.

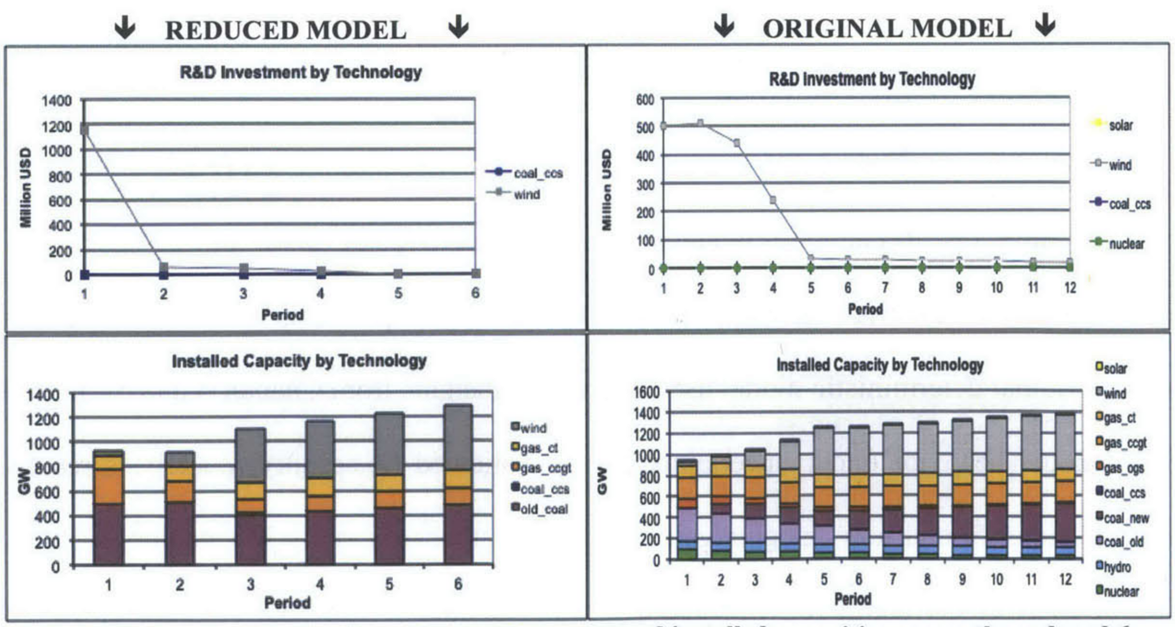


**Figure D-1 Comparison of optimal R&D investments and installed capacities across the reduced 6-period model (left) and the original model (right), under BAU**

Figure D-2 shows the optimal investment strategies across the two models under a moderate carbon target scenario (50% below BAU). The dominant changes seen in the original model when moving from a BAU scenario to a 50% below BAU carbon target scenario is the introduction of coal with CCS R&D investment, later term capacity additions of coal with CCS, and importantly, a phase-out of conventional coal new capacity additions. Each of these trends is witnessed in the reduced model as well. Coal with CCS R&D investments appear, and capacity is added in the later periods when it is absolutely necessary to meet the cumulative carbon cap. Note that the relatively gradual introduction of coal with CCS R&D compared with the wind R&D, and the lower peak coal with CCS R&D than peak wind R&D is also similar between the two models. Capacity additions for conventional coal are also phased out in the reduced model, as its high carbon emission rate no longer allows it to be a preferred technology under this more stringent cumulative cap.

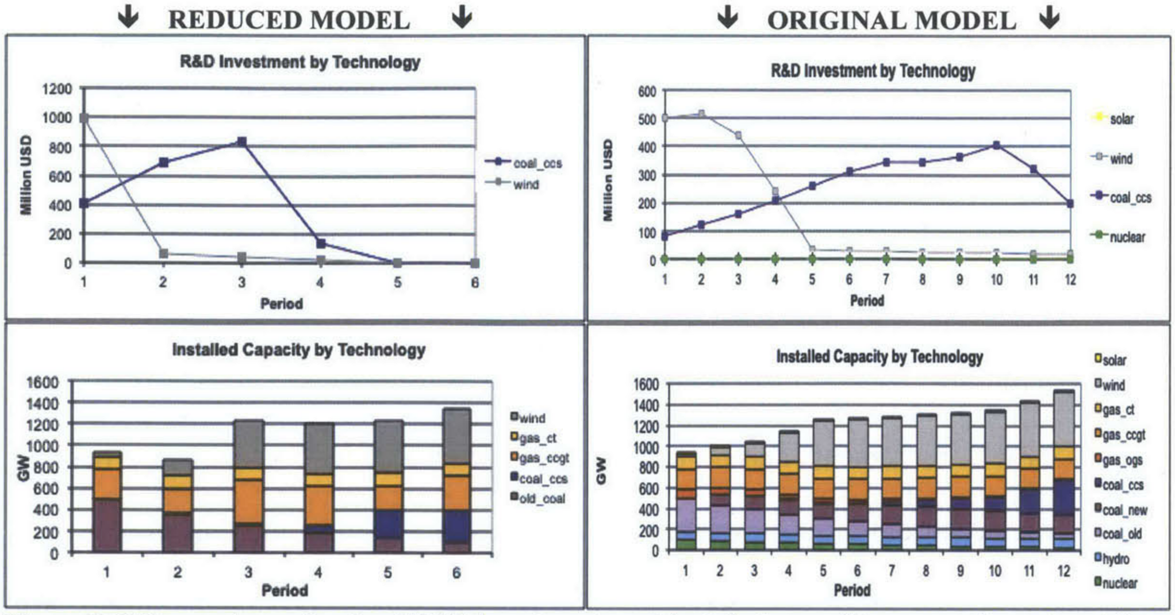


**Figure D-2 Comparison of optimal R&D investments and installed capacities across the reduced 6-period model (left) and the original model (right), under a 50% below BAU (MODERATE) carbon target**

One noteworthy dissimilarity between the two models is that in the reduced model, wind R&D investments decrease when a carbon target is imposed. In the original model, wind R&D investments are quite insensitive to changes in the carbon cap and other technology's R&D. The reason for this is that in the original model, the wind capital installment strategy is relatively unchanged between different carbon scenarios. It is a cheap source of zero-carbon electricity with a strong potential to learn (through both LBD and LBS), and thus plays an important role in the system with or without a carbon cap. In the original model, the installed capacity tends to reach the maximum capacity scale-up constraint in the early periods, and then levels out for the remainder of the problem horizon.

In the reduced model, however, the wind capital installment strategy exhibits non-negligible change across the carbon scenarios. Under BAU, most of the wind is installed in the second period (online in the third period), whereas under the moderate target a portion of this wind (30 GW) is built upfront in the first period (not visually observable in the graphs above). Wind plays this more flexible long-term planning role in the reduced model because of the lack of other zero-emission technologies available to help meet the caps. In the original model, the addition of nuclear power to the investment strategy was an option (for example), whereas in the reduced model wind and coal with CCS are the only two zero carbon options. Because coal with CCS reaches its capacity scale-up constraint, wind power becomes the only technology available to help meet additional more stringent carbon caps. The R&D investment pattern across carbon scenarios simply matches this need.

Under BAU, wind R&D investment is high because there is an opportunity to bring the capital cost of the technology down considerably before needing to install it later. Under a moderate target, wind R&D investment decreases because more of the capital investment must take place upfront to meet the cumulative emissions cap. While it is worthwhile to note that this difference in the two models exists, it does not signify a major structural or behavioral difference that would preclude the reduced model from providing insights during the stochastic analysis. Overall, the reduced model displays the same qualitative behavioral patterns as the original 12-period, 10-technology model.

## Part 2. Approximate Dynamic Program Validation

The second step in validating the numerical model used for the stochastic analysis is to ensure that the reference approximate dynamic programming (ADP) version of the new 6-period, 5-technology model produces similar results as the deterministic NLP model, when no uncertainty in technological change is present. Removing the uncertainty in the ADP approximates the deterministic solution. Table D-1 shows the resulting optimal decisions under each of the carbon target scenarios after 2000 iterations; Figure D-3 and Figure D-4 following the table present the results graphically.

**Table D-1 Comparison of Deterministic NLP and Deterministic ADP 6-Period Model Optimums**

| Model | **Stage 1 R&D** | **Stage 2 R&D** | **Stage 3 R&D** | **Stage 4 R&D** | **Stage 5 R&D** | **Stage 6 R&D** |
|---|---|---|---|---|---|---|
| **COAL WITH CCS** | | | | | | |
| **BAU** | | | | | | |
| *NLP* | 0 | 0 | 0 | 0 | 0 | 0 |
| *ADP* | 0 | 0 | 0 | 0 | 0 | 0 |
| **Moderate Cap** | | | | | | |
| *NLP* | 410.92 | 689.32 | 838.46 | 136.55 | 0 | 0 |
| *ADP* | 361.32 | 650.28 | 365.72 | 22.24 | 0 | 0 |
| **WIND** | | | | | | |
| **BAU** | | | | | | |
| *NLP* | 1162.04 | 62.12 | 44.06 | 24.23 | 0 | 0 |
| *ADP* | 946.36 | 106.60 | 81.60 | 33 | 0 | 0 |
| **Moderate Cap** | | | | | | |
| *NLP* | 991.00 | 62.28 | 44.17 | 24.28 | 0 | 0 |
| *ADP* | 887.52 | 0 | 24.72 | 33.12 | 0 | 0 |

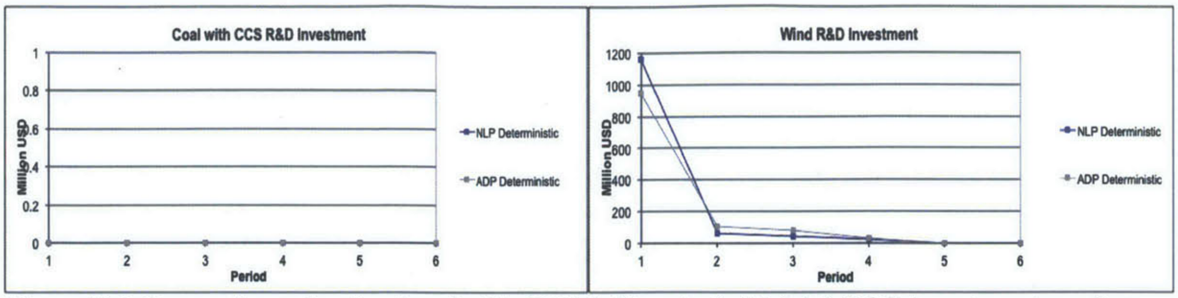

**Figure D-3 Comparison of optimal coal with CCS (left) and wind (right) R&D investment results from deterministic NLP and ADP models under BAU**

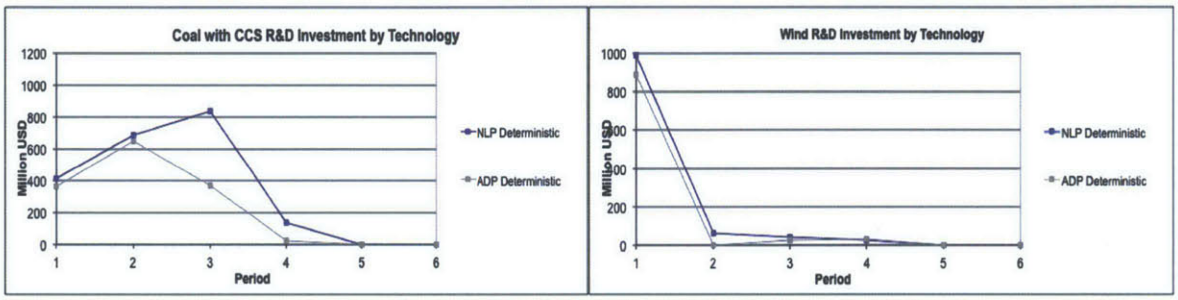

**Figure D-4 Comparison of optimal coal with CCS (left) and wind (right) R&D investment results from deterministic NLP and ADP models under a carbon target (50% BAU).**

Under BAU, the resulting first-period optimal decisions from the ADP version consistently converge to within approximately 20% of the NLP optimal decision. Under the imposed carbon target, convergence between the ADP and NLP first-stage optimal solutions narrows to within approximately 10% for both technologies. Additionally, the direction and magnitudes of the ADP results are consistent over different runs, and the qualitative behaviors for the R&D investment decisions across all time periods match the deterministic results.

Under BAU, the deterministic results display wind R&D investment only. Moreover, this investment occurs at a relatively aggressive rate in the first period, followed by a dramatic decline in later periods. The ADP results match this pattern (Figure D-3). Under the carbon cap, the major behavioral change in the deterministic results is that coal with CCS R&D enters, but at only about half the magnitude as the wind R&D investment. This is consistent with the ADP results, as coal with CCS R&D is present under the carbon cap, but is only \$361M versus the \$888M wind R&D investment. Additionally, first-period wind R&D decreases from the BAU to the carbon cap scenario in the deterministic NLP—a pattern that is replicated in the ADP with no uncertainty.

Overall, while quantitative (magnitude-based) differences are present between the deterministic NLP and ADP with no uncertainty, they are relatively minor, and qualitative behaviors match well. However, for the purposes of analysis and interpretation in Chapters 6 and 7, all results from the stochastic analysis that discuss the effect of uncertainty on the optimal investment strategy are benchmarked against the "deterministic" solution from the ADP with no uncertainty model to eliminate a potential bias.

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