Long Term Infrastructure Investments Under Uncertainty in the Electric Power Sector Using Approximate Dynamic Programming Techniques

by

Michael Seelhof
M.S. Mathematics (1994)
Justus Liebig Universität

Submitted to the System Design and Management Program
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Signature of Author

Michael Seelhof
System Design and Management Program
January 2014

Certified by

Mort Webster, Ph.D.
Thesis Supervisor
Engineering Systems Division

Accepted by

Patrick Hale
Director
System Design & Management Program
ABSTRACT

A computer model was developed to find optimal long-term investment strategies for the electric power sector under uncertainty with respect to future regulatory regimes and market conditions.

The model is based on a multi-stage problem formulation and uses approximate dynamic programming techniques to find an optimal solution.

The model was tested under various scenarios. The model results were analyzed with regards to the optimal first-stage investment decision, the final technology mix, total costs, the cost of ignoring uncertainty and the cost of regulatory uncertainty.

Thesis Supervisor: Mort David Webster
Title: Associate Professor of Engineering Systems
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Chapter 1

Introduction

1.1 Problem definition

The electric power sector is undergoing massive transformations. On the one hand, many existing generating assets will soon reach the end of their useful lifetime. On the other hand, stricter environmental regulations might force some operators to replace assets early. These transformations will thus soon create the need for substantial investments in new generating assets.

Investors in generating assets however are confronted with major uncertainties, including: (i) what will be the shape of future regulation and how will environmental requirements and greenhouse gas emissions restrictions impact the economics of generating technologies? (ii) how will technological progress influence the competitiveness of emerging technologies such as solar, wind, or carbon capture and sequestration? (iii) how will commodity prices impact the relative attractiveness of generating technologies and their role in the dispatch process.

Governments around the world have liberalized their electricity markets in the last two decades. Ownership of generating assets and investment decision processes now typically reside with private investors, while governments rely on policy instruments to ensure cost efficiency, security of supply, and environmental sustainability [1, 2, 3, 4].

The need for cleaner electricity generation has created a new trend towards non-market related policies by which regulators encourage or discourage specific technologies or fuels via, for example, technology mix targets, technology
specific emission limits [5], or outright banning of certain technologies.

Given the impact of these policies on investment decisions, it is crucial for
policy makers to understand how existing and potential policies, in combina-
tion with technological and market price uncertainties, impact costs, security
of supply, and environmental footprint of generation infrastructures. In this
respect, near-term investment decisions, taken under uncertainty, are of par-
ticular relevance.

This thesis develops a framework to find an optimal near-term technology
mix under regulatory, technological, and market price uncertainty, given
future ability to learn and adapt with additional investment decisions (re-
course).

1.2 Literature review

Classic approaches to capacity expansion under uncertainty use a two-stage
formulation. In stage 1, a capacity investment is chosen under uncertainty.
In stage 2, uncertainty is then fully removed by revealing a specific environ-
ment, the built capacity is operated and the objective function is evaluated
under the specific environment [6]. This formulation of the problem has
delivered useful results for generation expansion with transmission planning
and market design. However, it does not capture the sequential nature of de-
cision making, where learning between steps leads to adaptations of behavior.
As a consequence, the approach fails to explain the hedging strategies that
rational agents follow in their near-term decisions under uncertainty.

Recent extensions of the classic two-stage model therefore incorporate in-
vestment decisions in both stages. Typically, the second investment decision
is taken after uncertainty has been removed completely. Hu and Hobbs
[7] model a two-stage decision making process, influenced by three uncer-
tainties: electricity demand growth, natural gas prices, and greenhouse gas
regulations. They use a stochastic version of MARKAL to model these un-
certainties via a limited set of possible future scenarios. Decisions are made
in two stages: decision one ("here and now") with no knowledge of the fu-
ture, decision two ("wait and see") with full knowledge of the future (after
revealing which of the predefined scenarios materialized). Hu and Hobbs
analyze the price differentials of possible decision making strategies with a
particular focus on the expected value of perfect information (EVPI) and
the expected cost of ignoring uncertainty (ECIU).

9
Bistline and Weyant [8] implement a two-stage expansion process, taking into account uncertainty with regards to a future emissions cap and availability of carbon capture and sequestration (CCS). They apply stochastic programming in stochastic MARKAL. Bistline and Weyant focus both on cost metrics (value of the stochastic solution, expected value of perfect information, value of control) and the technology mix arising from the first-stage investment decision.

Stochastic MARKAL is a parameter-rich framework widely used in the field of capacity expansion analysis. It is however limited particularly with respect to uncertainty modeling and decision making by allowing only a maximum of nine deterministic scenarios and two decision stages simultaneously. Models based on stochastic MARKAL are therefore typically restricted to two or three uncertainties with two or three predefined values each ("high"/"medium"/"low", or "high"/"low"). In addition, stochastic MARKAL is limited with respect to the parameters that can be treated as random. While environmental bounds and demand can be modeled as uncertain, technological parameters such as capital costs are treated as constant. Lastly, decision dependency, where a decision influences the future state of the system, cannot be modeled.

Fan et al [9] examine the impact of risk aversion and uncertainty in the design of a cap-and-trade policy (auction vs. grandfathering of permits) on capacity expansion decisions made by two independently operating agents choosing from two technologies in a classical two-stage process. A specific regulation is revealed after investors have taken their expansion decisions. Fan et al specifically focus on the effect of regulatory uncertainty. No further stochastic behavior is introduced.

Examples of multi-stage (more than two) models are limited. Pereira et al [10] have used SDDP decomposition approaches to multi-stage planning, for uncertainties in demand and fuel prices.

### 1.3 Question and approach

This thesis presents a multi-stage, central generation expansion model with uncertainties in future greenhouse gas emissions restrictions, natural gas prices, and the costs of several low-carbon technologies that evolve as random walks. The computational challenges from the dimensionality are addressed
with an approximate dynamic programming algorithm that uses a mesh-free approximation of the cost-to-go function.

Results include traditional measures such as the value of the stochastic solution and the cost of ignoring uncertainty, with a focus on the technology mix in the first stage. It is shown that the optimal hedging strategy in the near-term includes larger shares for most alternative generation technologies than the deterministic optimal solution, which has important implications for current regulatory debates. As an example for command-and-control policies, scenarios are run in which certain technologies—particularly nuclear and coal—are excluded entirely from the portfolio of available technologies. Finally a comparison of the near-term mix from a two-stage and a three-stage formulation demonstrates that models with multiple investment stages that react to the evolution of stochastic processes provide critical insights into the question of what technology mix needs to be encouraged by decision makers.

1.4 Thesis structure

This thesis is organized in six chapters.

Following the introduction, chapter 2 provides an overview of the electric power sector. It describes the sector’s major functions, discusses the state and impact of deregulation, and regional differences. It also explains the characteristics of the major generating technologies and concludes with an overview of the main challenges that the sector is facing around the world. The chapter lays the necessary foundation for the problem’s understanding.

Chapter 3 defines the problem and hypotheses tested. It motivates the chosen approach of gradually increasing the amount of (regulatory and market) uncertainty and concludes with a formal description of the parameters and rules that comprise the model.

Chapter 4 presents the chosen solution approach. It explains the choice of approximate dynamic programming (ADP) and provides a high-level description of the key elements of the algorithm.

Chapter 5 presents the simulation results in six steps: (i) the deterministic cases serve as basis for all further steps. Optimal capacity expansion strategies are presented for five different, deterministic carbon caps. The deter-
ministic cases are solved using both the approximate dynamic programming approach and a standard, non-linear programming formulation (NLP). The two approaches deliver very similar results, which validates the ADP model. This validation approach is limited to the deterministic cases since the fully stochastic three-stage model introduced in the succeeding steps would not computationally tractable using conventional LP or NLP formulations. (ii) Regulatory uncertainty is introduced in the form of uncertain carbon caps. The solutions to these cases are examined both with respect to the actual capacity expansion strategy and the resulting cost distributions. The model results are analyzed with respect to technology-specific investment decisions and cost profiles. Costs are compared with the deterministic results and the concept of "cost of regulatory uncertainty" is introduced. (iii) In a third step, market uncertainty is introduced in two ways: firstly, natural gas prices are modeled as a stochastic process, influencing the operating cost of generating technologies; secondly, capital costs for emerging technologies are modeled as a one-factor learning curve, leading to construction costs per unit of these technologies decreasing with the respective past cumulative construction (installed base). (iv) The fourth step combines regulatory and market uncertainty in one scenario and examines how the combination particularly impacts the choice of low-carbon technologies. Both the cost of ignoring uncertainty and the cost of regulatory uncertainty are calculated. (v) In a fifth step, nuclear and coal are excluded individually and combined from the portfolio of available technologies. The scenarios are evaluated both under full uncertainty and under market uncertainty only. (vi) The sixth step compares the results of the chosen three-stage approach with those of a two-stage formulation. The section focuses on model behavior that emerges from a multi-stage formulation but cannot be observed in a two-stage setting.

Finally, chapter 6 summarizes the major findings and suggests future areas of research based on the model developed in this thesis and proposes potential model extensions.
Chapter 2

The electric power sector

Electricity is an essential source of economic activity in all modern societies. More than 36% of the energy produced globally in 2011 was used to generate electricity [11].

Complex generation, transmission and distribution infrastructures have become increasingly interconnected across geographic and political boundaries. Accordingly, Expósito et. al. call the global electric energy systems "the biggest industrial system created by humankind" [12].

This chapter lays the foundation for the problem formulation introduced in chapter 3 and introduces the industry-specific concepts and technologies that are crucial for the understanding of the subject.

This chapter is organized in two parts. The first part gives an overview of the organization of the power sector, its key decision making processes from real time operations to long term strategic planning, and the characteristics of the major generating technologies. The second part summarizes the sector's most important trends and challenges.
2.1 Structure of the electric power sector

2.1.1 Organization of the industry

The industry can be broken down into four main parts: generation, transmission, distribution, and consumption.

Generation

Generation is concerned with the production of electric power.

Production technologies can be grouped into fossil-fuel based, nuclear, and renewable generation (see 2.1.3 for details by technology). Technologies differ largely with respect to regional availability, operational aspects, economics, and environmental impact. These differences explain why technology mixes vary widely by country, why grid operators typically rely on a balanced mix of various technologies, and why economies continue to invest in a wide range of technologies that are uneconomical today.

Regional availability of energy sources differs widely and governs in many cases whether a region or country can develop a certain technology economically. This is particularly true for renewable sources such as hydro, wind, solar and biothermal. However, restrictions also apply to fossil fuels that cannot easily be imported, such as natural gas. To the extent economical import options are available, a country might still decide to restrict its dependence on such imports for political reasons. Finally, a region might be limited with respect to the secondary means of production. The exploration of natural gas, for example, requires large amounts of water. This can represent challenges to water-constrained countries such as China.

Technologies also differ with respect to operational aspects and economics. It is, for example, costly and time-consuming to start up nuclear and coal power stations. Both technologies require substantial upfront capital investments and have relatively low marginal costs. Nuclear and coal plants are therefore ideal candidates for the delivery of base load demand, the level of demand that will exist with a high level of certainty throughout a year. Gas combustion turbines, on the other hand, can be brought online within minutes and are inexpensive to build, but they are expensive to operate. Consequently, these stations will usually be operated during peak demand
periods only. Lastly, wind turbines and solar plants can be operated at virtually zero marginal cost and involve large capital commitments, but energy supply is intermittent. Larger operating reserves consisting of traditional power generators are therefore required to ensure uninterrupted supply during periods of low output from renewables. This represents an additional cost of renewable energy generators. Differences with respect to operations and cost structures explain why grid operators typically deploy a portfolio of technologies that fulfill different roles.

Electric power generation has a large impact on the environment, most prominently through the generation of greenhouse gases: electricity production contributed 40% to worldwide carbon dioxide emissions from fuel combustion in 2010 [13]. The environmental impact of electric power generation extends beyond the emission of greenhouse gases however: combustion produces air pollutants other than CO₂; nuclear power generation produces radioactive waste and can lead to potentially catastrophic accidents; both fossil-fuel based and nuclear generators consume large amounts of water; hydro dams require the flooding of vast areas; wind farms can have unintended consequences on natural habitats; large-scale solar installations occupy large stretches of land; manufacturing of photovoltaic cells is energy-intensive and creates pollutants; all generating activities require substantial off-site infrastructure which further impacts the environment, e.g. through the transportation of fuel and waste and transmission of electricity. Changes in future regulation, such as CO₂ emission restrictions, might strongly impact the economic viability of certain technologies or even lead to the ban of a certain technology¹. A balanced portfolio of different technologies provides system operators and investors with a natural risk diversification against regulatory changes. Furthermore, clean technologies that cannot compete financially with established, more polluting technologies today, might become attractive options under stricter environmental laws in the future. For that reason, most large economies heavily invest in the research, development, demonstration and deployment of a wide range of new technologies.

Transmission

Transmission networks transport electricity—often across long distances—from the point of generation to the end user. Networks consist of high-voltage

¹This is for example the case for new conventional coal plants in the United States or nuclear plants in Germany.
transmission lines and substations. A typical transmission network has a web-like structure with redundant lines and stations to improve the system's resilience in the case of equipment failure. Substations transform voltage to higher or lower levels and eventually feed into the distribution networks. Substations also comprise control infrastructure that allows operators to monitor system performance and isolate failed equipment from the network.

Transmission networks have grown more and more connected over time across large regions and across national boundaries. This has contributed to the stability of power grids and has enabled operators to share resources with connected grids. Connectivity of transmission infrastructure is also an important precondition for the economic deployment of renewable resource-based generation capacity at a large scale (see section 2.2.3).

Distribution

Distribution networks connect the high-voltage transmission network to the end user. Distribution networks are lower-voltage networks and are usually organized radially with little redundancy. Consequently, they are the most frequent source of power outages. Since distribution networks, particularly in urban areas, are usually dense and mostly built underground, construction and maintenance costs are much higher than those of transmission networks.

Consumption

Demand for electricity is considered a clear indicator of a country’s economic development and correlates strongly with a country’s gross domestic product. While long-term development of demand directly influences expansion decisions, short-term demand fluctuations have a strong impact on the operations of a network.

Global demand for electricity has increased by 81% from 1990 to 2010, from 11,819 TWh to 21,397 TWh [13]. This increase has been strongly driven by the economic growth of developing countries. China alone grew by 548% and represented 20% of global production in 2010 (up from 5% in 1990). Developed countries have grown at a much slower pace but from much higher levels. The United States and the European OECD members for example each grew by 34% from 1990 to 2010 (see Figure 2.1).
To satisfy growing demand, frequent expansion of generation and transmission infrastructure is required. The related large upfront investments strongly impact the economics of a network. Accordingly, comprehensive long-term demand forecasts are a crucial element of strategic planning. Forecasts typically cover uncertainties stemming from economic growth, from increased energy efficiency of production processes and appliances, but also from new consumers such as electric vehicles.

Short-term fluctuations of electricity demand mostly follow seasonal (see Figure 2.2), weekly, and daily (see Figure 2.3) patterns, driven by industrial clients and retail customers alike. In the absence of scalable storage solutions, supply needs to meet demand at all times. This is the role of economic dispatch and unit commitment (see section 2.1.2). Real-time and short-term load balancing and dispatch activities strongly impact both the stability of a power grid and cost of operations. Considerable research is therefore committed to the understanding and forecasting of short-term demand patterns. In addition, demand side management (DSM) is increasingly used to incentivize customers to curtail their energy consumption during periods of peak demand.
Figure 2.2: Daily demand for a full year, ERCOT region, 2012 [14]

Figure 2.3: Average daily demand per month, ERCOT region, 2012 [14]
2.1.2 Planning and operations

The management of the electric power sector is distributed across many participants and ranges from real time operational decisions to long term planning activities (see Table 2.1).

<table>
<thead>
<tr>
<th>Time scale</th>
<th>Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real time</td>
<td>Protection</td>
</tr>
<tr>
<td></td>
<td>Generation control</td>
</tr>
<tr>
<td>Short term (up to one month)</td>
<td>Short term load forecasting</td>
</tr>
<tr>
<td></td>
<td>Economic dispatch</td>
</tr>
<tr>
<td></td>
<td>Unit commitment</td>
</tr>
<tr>
<td></td>
<td>Hydro scheduling</td>
</tr>
<tr>
<td>Medium term (up to three years)</td>
<td>Medium term load forecasting</td>
</tr>
<tr>
<td></td>
<td>Maintenance scheduling</td>
</tr>
<tr>
<td></td>
<td>Fuel management</td>
</tr>
<tr>
<td></td>
<td>Management of limited resources other than fuel</td>
</tr>
<tr>
<td>Long term (beyond three years)</td>
<td>Long term forecasting of key parameters</td>
</tr>
<tr>
<td></td>
<td>Expansion planning</td>
</tr>
</tbody>
</table>

Table 2.1: Activities in planning and operations

Real time decisions

Real time operations focus on activities that ensure the stability of the system and minimize failures. Because of the short reaction times involved and the importance to the stability of the system, real time operational management today is highly automated.
Automatic circuit breakers have a major role in system protection since they isolate faulted components with minimal disturbance to the connected system. System protection also includes the provision of backup transmission routes and generating capacity.

Generation control is the process of regulating generation output with the aim to closely match the demand fluctuations at all times. With automated generation control, many generation units typically contribute jointly to output adjustment, thus reducing the wear on a single generator (before automated controls, one generator would be designated as the regulating unit).

**Short term decisions**

Short term decisions range from a day to a month. The most important activities in that time period are concerned with load forecasting and scheduling generating stations.

*Short term load forecasts* attempt to accurately predict demand profiles for up to a week. Sophisticated statistical models are able to predict demand for the following days with an error between 1 and 3%. Important input factors for short term load forecasts include time of day, day of the week, current season, and weather data [15].

The second step, *economic dispatch*, is the process of finding the cheapest way to satisfy the predicted demand profile with the existing fleet of generators. The marginal costs of the various generating units represent the main inputs into the economic dispatch.

The last step in the scheduling process, *unit commitment*, is concerned with finding the optimal scheduling of the available power stations, based on the results of the economic dispatch and the actual states of each station (hot / cold / intermediate), their startup costs, startup time, minimum run time, and minimum down time. Hydro resources have a pronounced role in the scheduling process given that their startup time is virtually zero, and their availability is naturally limited.
Medium term decisions

Medium term decisions cover the period of a month up to approximately three years. Their main focus is the management of available resources to achieve cost efficiency and comply with defined safety and quality standards.

As is the case for short term planning, a crucial element of medium term decision making is load forecasting. *Medium term load forecasting* relies on similar variables as short term forecasting.

*Maintenance scheduling* is concerned with coordinating scheduled downtimes of all generating assets and transmission assets of a network. Schedules take into account the medium term load forecasts to ensure sufficient supply at all times.

*Fuel management* comprises acquisition, transportation, and storage of fuel. In addition to load forecast results, important input factors to fuel management are current and forecasted market prices for fuel and transportation, and storage capacity.

Finally, medium term decision making includes the management of other limited resources, which includes means of production (such as water used for cooling), but also regulatory factors such as emissions allowances. These resources will govern if and to what extent existing generating resources are utilized.

Long term decisions

Long term decision making is primarily concerned with capacity expansion. Uncertainties are greatest in this domain, given the long planning horizon. Capacity expansion decisions also have the highest impact on the future economics of a network, given the large capital commitments involved and long asset lifetimes.

*Long term forecasts* that take into account the key parameters influencing the economics of a network are therefore a crucial component of decision making for capacity expansion. Important uncertainties include the development of demand, fuel prices, technological progress, and availability of resources. In addition, regulatory actions can massively influence the economics and viability of a given technology mix.
Capacity expansion decisions need to take into consideration a wide range of potential future scenarios. Resulting strategies will therefore usually comprise the building of a mix of different technologies which is optimized for the range of considered scenarios as opposed to a strategy which is optimal for a specific, expected scenario.

2.1.3 Generating technologies

This section gives an overview of the major technologies in use today.

In April 2013 the U. S. Energy Information Administration (EIA) published updated cost and efficiency figures for a comprehensive range of generating technologies [16]. The model presented in the following chapters is based on these parameters. Table 2.2 shows the full list of technologies covered by the EIA.

Coal-fired power generation

The core of a coal-fired power station is a boiler which produces steam by burning coal. The high pressure of the steam drives a steam turbine, and the kinetic energy of the steam turbine is converted into electric power by a generator.

Coal is the dominant source for power generation world-wide: in 2011 coal represented 48% of the total energy consumed by electric power stations (measured by energy content, [11]), and coal-fired power stations produced 41% of the world’s electricity [17].

Coal is a low-cost and abundant source of energy. Generation can easily be scaled and the useful lifetime of a generator typically exceeds 40 years. However, to operate a plant, substantial infrastructure is required. Typical generators are therefore large with nominal capacities of a single unit of 650 MW and a dual unit of 1,300 MW. Coal plants cannot be brought online quickly, since it takes several hours to heat up the boilers from cold condition. This, combined with relatively low marginal costs, has made coal generation the preferred base-load technology in most environments. Coal plants—with the exception of maintenance down-times—have traditionally run on full capacity permanently.

The major disadvantage of traditional coal-fired power generation is its large
<table>
<thead>
<tr>
<th>Energy source</th>
<th>Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>Advanced pulverized coal generation</td>
</tr>
<tr>
<td></td>
<td>Advanced pulverized coal generation with carbon capture and sequestration</td>
</tr>
<tr>
<td></td>
<td>Integrated gasification combined cycle with carbon capture and sequestration</td>
</tr>
<tr>
<td></td>
<td>Integrated gasification combined cycle with carbon capture and sequestration</td>
</tr>
<tr>
<td>Natural gas</td>
<td>Conventional combined cycle</td>
</tr>
<tr>
<td></td>
<td>Advanced combined cycle</td>
</tr>
<tr>
<td></td>
<td>Advanced combined cycle with carbon capture and sequestration</td>
</tr>
<tr>
<td></td>
<td>Conventional combustion turbine</td>
</tr>
<tr>
<td></td>
<td>Advanced combustion turbine</td>
</tr>
<tr>
<td></td>
<td>Fuel cells</td>
</tr>
<tr>
<td>Uranium</td>
<td>Advanced nuclear</td>
</tr>
<tr>
<td>Wind</td>
<td>Onshore wind</td>
</tr>
<tr>
<td></td>
<td>Offshore wind</td>
</tr>
<tr>
<td>Solar</td>
<td>Solar thermal</td>
</tr>
<tr>
<td></td>
<td>Solar photovoltaic</td>
</tr>
<tr>
<td>Hydroelectric</td>
<td>Conventional hydroelectric</td>
</tr>
<tr>
<td>Biomass</td>
<td>Pumped storage</td>
</tr>
<tr>
<td></td>
<td>Biomass combined cycle</td>
</tr>
<tr>
<td></td>
<td>Biomass bubbling fluidized bed</td>
</tr>
<tr>
<td>Geothermal</td>
<td>Geothermal dual flash</td>
</tr>
<tr>
<td></td>
<td>Geothermal binary</td>
</tr>
<tr>
<td>Municipal solid waste</td>
<td>Municipal solid waste</td>
</tr>
</tbody>
</table>

Table 2.2: EIA list of power plant technologies [16]
carbon dioxide footprint. Coal accounted for 45% of total energy-related CO₂ emissions in 2011 [18].

Research has therefore focused on scrubbing systems that can capture large parts of the carbon from a coal plant’s flue gas. In a second step, the captured carbon would be compressed and sequestered permanently, normally in an underground geological formation. Although coal plants with such carbon capture and sequestration (CCS) technology have a higher heat rate than regular coal plants and thus consume more coal to produce the same amount of energy, the technology is expected to reduce carbon emitted to the atmosphere by 80 – 90%. Coal CCS technology is reliant on the availability of safe underground storage facilities and ways to transport compressed carbon from the production sites to these storage facilities. The Energy Information Agency therefore estimates that CCS technology increases capital costs for a coal plant by about 63% [16]. With continued investments in research and development and experience gained through construction of plants, that cost differential is expected to decrease. However, no full-scale coal CCS plants have been built in the world to date.

Table 2.3 presents key parameters for coal-fired technologies. For further detail see appendix A.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Advanced pulverized coal generation</td>
<td>3.2</td>
<td>0.038</td>
<td>21.9</td>
<td>0.823</td>
</tr>
<tr>
<td>Advanced pulverized coal generation with carbon capture and sequestration</td>
<td>5.2</td>
<td>0.081</td>
<td>33.3</td>
<td>0.112</td>
</tr>
<tr>
<td>Integrated gasification combined cycle</td>
<td>4.4</td>
<td>0.062</td>
<td>24.4</td>
<td>0.814</td>
</tr>
<tr>
<td>Integrated gasification combined cycle with carbon capture and sequestration</td>
<td>6.6</td>
<td>0.073</td>
<td>29.6</td>
<td>0.100</td>
</tr>
</tbody>
</table>

Table 2.3: Key parameters for coal-fired technologies [16]²
Gas-fired power generation

Gas-fired power stations belong—like coal-fired stations—to the family of thermal plants: a gas turbine produces high-pressure steam; the steam drives a steam turbine; and an electric generator finally converts the mechanical energy of the turbine into electric power. While traditional, single-cycle combustion engines produce a significant amount of unused heat, modern combined cycle gas generators make use of a second heat engine to convert the engine’s exhaust heat into additional electric power.

In 2011 gas represented 22% of the total energy consumed by electric power stations (measured by energy content, [11]), and gas-fired power stations produced 22% of the world’s electricity [17].

Like coal-based production, most components of a gas-fueled generator are considered mature technology. Gas generators have a significantly smaller physical footprint (among other factors, and in contrast to coal, gas is not stored on-site) and are cheaper to build. In addition, start-up times are much shorter since gas generators do not possess the heat inertia introduced by the large boilers of a typical coal power plant. Traditionally, due to the price difference between gas and coal and due to the lower efficiency of single-cycle gas combustion engines, the marginal costs of operating a gas plant were significantly higher than those of a coal power plant. Because of these characteristics, the main role of conventional combustion turbines has been to satisfy demand peaks during a day. Combined cycle plants were typically used as intermediate power generators due to their higher efficiency.

However, the current shale gas revolution in the United States (see section 2.2.4) has almost fully eliminated the marginal cost disadvantage of advanced combined cycle gas turbines in comparison to coal generation. Based on current fuel prices in the United States, modern combined cycle gas stations compete with coal generators as base load technology.

The major advantage of gas over coal, however, is its much lower carbon content: To produce the same amount of electrical power, combined cycle gas plants emit about 60% less carbon than coal generators.

Table 2.4 presents key parameters for gas-fired technologies. For further detail see appendix A.

---

2 Assumptions: price of coal: $1.98 / MMBtu, carbon content of coal: 93.5 kg per MMBtu, carbon capture through CCS: 90%, heat rate APC without (with) CCS: 8.8 (12.0) MMBtu per MWh
### Table 2.4: Key parameters for gas-fired technologies [16]³

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional combined cycle</td>
<td>0.9</td>
<td>0.013</td>
<td>31.8</td>
<td>0.374</td>
</tr>
<tr>
<td>Advanced combined cycle</td>
<td>1.0</td>
<td>0.015</td>
<td>29.0</td>
<td>0.342</td>
</tr>
<tr>
<td>Advanced combined cycle with carbon capture and sequestration</td>
<td>2.1</td>
<td>0.032</td>
<td>36.9</td>
<td>0.041</td>
</tr>
<tr>
<td>Conventional combustion turbine</td>
<td>1.0</td>
<td>0.007</td>
<td>58.9</td>
<td>0.576</td>
</tr>
<tr>
<td>Advanced combustion turbine</td>
<td>0.7</td>
<td>0.007</td>
<td>49.4</td>
<td>0.518</td>
</tr>
<tr>
<td>Fuel cells</td>
<td>7.1</td>
<td>0.000</td>
<td>81.0</td>
<td>0.561</td>
</tr>
</tbody>
</table>

³Assumptions: price of gas: $4 / MMBtu, carbon content of gas: 53.1 kg per MMBtu, heat rate CCGT (CT): 6.43 (9.75) MMBtu per MWh

**Hydroelectric power generation**

Hydroelectric power stations use the gravitational energy of flowing water to run a hydraulic turbine. A generator transforms the mechanical energy of the turbine into electricity. There are four main categories of hydroelectric power generation: (i) conventional dams, (ii) run-of-the-river, (iii) tidal, and (iv) pumped storage. Pumped storage sites use an elevated reservoir to which water is pumped in times of low electricity demand. The pumped water can then be used during peak demand times to generate electricity. Pumping power stations are therefore typically categorized as a storage technology rather than a means to produce electricity.

With a contribution of over 16% in 2011, hydroelectric power is the third largest source of electricity world-wide. Current projects under construction will increase capacity by c. 18%, and experts estimate that there is large, untapped and economically attractive further potential.

Where geographically viable, hydropower offers many advantages: (i) elec-
tricity generation can quickly and easily be turned on and off; (ii) generation is free of greenhouse gas emissions; (iii) pumping power stations provide means to store energy. As a negative, construction is expensive and usually involves flooding of large (often inhabited) regions.

Table 2.5 presents key parameters for hydroelectric technologies. For further detail see appendix A.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conventional hydroelectric</td>
<td>2.9</td>
<td>0.014</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Pumped storage</td>
<td>5.3</td>
<td>0.018</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Table 2.5: Key parameters for hydroelectric technologies [16]

**Nuclear power generation**

Similar to fossil-fuel based electricity production, nuclear power generation is steam-based. Nuclear reactors use atomic fission of enriched uranium to heat large amounts of water. The remaining process steps are in principle similar to fossil-fuel based generation.

Nuclear power generation represented 12% of the world’s power generation in 2011.

The economics of nuclear power generation include high capital costs and extremely low variable costs. Starting up and shutting down nuclear power stations is extremely complex and dangerous because of the changes to the cooling conditions in the reactor. Nuclear power stations therefore always have the role of base load generators and—with the exception of scheduled maintenance—need to operate permanently.

A large advantage of nuclear power generation is the fact that no greenhouse gas emissions are being produced. However, nuclear power has been opposed in some countries due to (i) the risk of catastrophic accidents such as the
ones at Three Mile Island (U.S.A., 1979), Chernobyl (Russia, 1986), and Fukushima (Japan, 2011), and (ii) the radioactive waste produced.

Table 2.6 presents key parameters for nuclear technologies. For further detail see appendix A.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear dual unit</td>
<td>5.5</td>
<td>0.093</td>
<td>4.2</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2.6: Key parameters for nuclear-based technologies [16]

Wind-powered generation

Large-scale wind-based power generators consist of farms of wind turbines. Individual wind turbines typically comprise a three-blade rotor attached to a nacelle on top of a steel tower. The nacelle contains a variable-speed generator which transforms the kinetic energy into electricity. Modern large turbines for on-shore use typically range in output ("rated power") from 1 MW to over 3 MW, with rotor diameters between 70 m and more than 120 m. Turbines deployed in offshore wind farms are typically larger both in output (up to 8 MW) and rotor diameters (the largest exceeding 160 m).

Wind power contributed 2.1% to global energy production in 2011. The installed base is growing rapidly at an annual rate of 25% [21]. After hydro, wind power is the second-most important renewable energy source for electricity.

The economics of wind generation include normalized capital costs and fixed annual O&M costs that are about twice as high as those of a combined-cycle gas station. However, the marginal cost of wind generation is zero [16].

Wind generation is desirable from an environmental perspective, since it does not produce greenhouse gas emissions. However, as an intermittent source

---

4 Assumptions: price of 3.2% enriched uranium $0.19 per MMBtu, heat rate of a nuclear station 10.46 MMBtu per MWh (sources: [19], [20])

28
of energy, wind generation on a large scale introduces different challenges and involves additional costs since it requires operators to provide sufficient, reliable backup generating capacity that can quickly be brought online during phases of low wind output (see section 2.2.3).

Table 2.7 presents key parameters for wind-powered technologies. For further detail see appendix A.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Onshore wind</td>
<td>2.2</td>
<td>0.040</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Offshore wind</td>
<td>6.2</td>
<td>0.074</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 2.7: Key parameters for wind-powered technologies [16]

**Solar-powered generation**

Solar-powered generation comprises two different concepts: solar thermal and photovoltaic.

*Solar thermal stations* (also known as concentrated solar power, "CSP") concentrate the sunlight to heat a fluid or gas which then is used to generate electricity. Three main CSP designs exist: the Dish/Stirling engine, the parabolic trough design, and the solar power tower design. Fluids include molten salt solutions, which can store heat for a period of time for later electricity generation, effectively working as a battery.

The development of large-scale solar thermal stations is still in demonstration stage. However, many projects are currently planned world-wide. The largest installation under construction to date is the Ivanpah Solar Power Facility in the California Mojave desert with a gross capacity of 392 MW.

Photovoltaic energy generation uses photovoltaic semiconductors to convert sunlight into direct current. Inverters convert direct current into alternating current for feed-in operations. Many large-scale installations exist, mainly in Europe. The largest site the Agua Caliente Solar Project in Arizona—has a gross capacity of 247 MW.
Solar-powered generation (almost exclusively photovoltaic) represented only 0.3% of world-wide electricity production in 2011, but the installed base is rapidly growing.

Normalized capital costs for solar-powered stations are four times as high as those for combined cycle gas generators. However, prices for solar panels have fallen considerably in the last years and marginal operating costs are zero. As an intermittent source of power, solar-powered electricity generation poses the same challenges to operators as wind generation (see section 2.2.3). However, solar thermal generation promises the ability to smooth output by temporarily storing energy in the form of heat (see above).

Table 2.8 presents key parameters for solar-powered technologies. For further detail see appendix A.

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solar thermal</td>
<td>5.1</td>
<td>0.067</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Solar photovoltaic</td>
<td>3.9</td>
<td>0.025</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2.8: Key parameters for solar-powered technologies [16]

Other technologies

Other means of electricity generation include the burning of biomass or municipal solid waste and the use of geothermal energy.

Biothermal power generation accounted for 1.3% of global electricity production in 2011, and the combustion of municipal solid waste for 0.3% of U.S. electricity production (no global figures available). Geothermal contributed 0.3% to electricity production world-wide.

Table 2.9 presents key parameters for these technologies. For further detail see appendix A.
<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass combined cycle</td>
<td>8.2</td>
<td>0.356</td>
<td>17.5</td>
<td>1.093</td>
</tr>
<tr>
<td>Biomass bubbling fluidized bed</td>
<td>4.1</td>
<td>0.106</td>
<td>5.3</td>
<td>1.195</td>
</tr>
<tr>
<td>Geothermal dual flash</td>
<td>6.2</td>
<td>0.132</td>
<td>-</td>
<td>0.054</td>
</tr>
<tr>
<td>Geothermal binary</td>
<td>4.4</td>
<td>0.100</td>
<td>-</td>
<td>0.054</td>
</tr>
<tr>
<td>Municipal solid waste</td>
<td>8.3</td>
<td>0.393</td>
<td>8.8</td>
<td>1.634</td>
</tr>
</tbody>
</table>

Table 2.9: Key parameters for other technologies [16]

2.2 Industry trends and challenges

2.2.1 Deregulation

Deregulation has been reforming the electric power sector in many countries around the world.

Chile was the first country to deregulate with the 1982 Electricity Reform. Most developed countries followed suit in 1990’s with national deregulation varying in structure and extent.

This section outlines the evolution of the regulation and organization of the electric power generation since its inception and explains the structure of the industry in a deregulated environment.

Historical context

The dominant organizational structure before deregulation was a large, vertically integrated utility under strong government control or under government ownership. Its origin can widely be explained by the technological development of electricity generation.

Because of the loss of power, electric power could not be transported over long distances initially. Consequently, electric power generation at the end of the
19th century was a very local and unconnected activity. At the turn of the century, transmission over long distances was made possible by transforming electricity from direct current to alternating current. Around the same time, technological advances (particularly the adoption of the turbogenerator) allowed for the output of single generators to increase dramatically. This laid the foundation for nationally connected networks which started to emerge in the 1920's in industrialized countries such as England (National Grid) or Germany (Nord-Süd-Leitung). Likewise, increasing economies of scale (originating from the growing interconnectedness of the grid), larger generator designs and the substantial investments required, led to the creation of large, vertically integrated electric utilities.

The importance of electricity for the rapid industrialization at the beginning of 20th, finally, explains why utilities in most industrializing countries were either heavily controlled or owned by the government.

The case for deregulation

In the 1990's, deregulation ended the dominance of the large, vertically integrated utility model in many countries around the world. This trend had economic, regulatory, and technological reasons.

The growing demand for electricity throughout the 20th century had created very large infrastructures comprising generating assets, transmission and distribution lines, under the control of a few heavily regulated or government owned entities. While benefiting from growing economies of scale, these entities had developed substantial inefficiencies in the absence of competition. In addition, where utilities were government owned, the government had a dual role of owner and regulator, leading to conflict of interest. As a result, many countries experienced an erosion of service quality with constantly rising costs, which slowed down economic progress.

Countries started to connect their transmission networks across country borders, allowing for import and export of energy. These countries benefited from more stable power supply and a more diversified access to natural resources such as hydro power generation. These transnational grids created a need and the opportunity for new regulation, since connectivity aspects could not be governed by the regulation of one member country alone.

Technology had meanwhile evolved both with respect to hardware and software. Metering and a growing number of control points were increasing the
amount of information available about the grid, and information technology provided the means to improve both planning and operations. More importantly, technology had created the opportunity to separate and decentralize management responsibilities.

Organization of deregulated markets

Deregulation has dramatically decentralized responsibilities for planning and operations. While countries have adopted different approaches to deregulation, the organizational separation of generation, transmission and distribution is common to most frameworks. Due to their structural differences, however, regulation differs substantially across the three basic functions. In a deregulated environment, certain functions such as electricity trading, real-time system operations, and regulatory oversight still require central coordination or controls.

Generation

Generation is structured as a deregulated activity, strictly separated from transmission and distribution.

Investors in generating assets take independent investment decisions. Generators act as independent agents in the energy market, deciding independently on the price and electricity they offer. They are also responsible for operational aspects such as maintenance scheduling and the procurement of resources.

Risk management is a crucial activity for investors in this environment. During the investment decision process, investors need to anticipate the impact of multiple, uncertain factors, such as changes in operating costs, demand levels, competitor activity and regulation, on a potential investment over its entire lifetime.

Investors also need to assess the opportunity cost of an investment in the electric power sector. Better opportunities in other industries or asset classes might divert investments away from the sector. This is a prevailing challenge for regulators around the world, and attempts to solve this challenge vary widely.
Transmission

Unlike generation, the economics of transmission networks naturally limit the amount of competition for that service. It is generally not economically viable or desirable to have duplicate transmission lines connecting two points. In a deregulated environment, transmission activities are therefore managed as a natural monopoly. The role of the regulator is to ensure fair and unrestricted access to the network for generators and distributors, adequate investments into the network and fair prices.

Access is usually granted via auctions with prices for access varying by nodes or zones.

Investments are controlled either (i) via a centralized planning approach; (ii) by giving full control to a single transmission company; or (iii) by allowing the users of the network—generators, industrial consumers, and distributors—to control the investment process.

Prices for transmission services are set such that they cover the cost of operations (particularly network infrastructure costs and ohm losses) and set incentives aimed at influencing the location of future generators and future sites of large industrial consumers.

Distribution

Distribution has two components which are regulated differently: (i) the provision of the physical connections to the end user, and (ii) the selling of electricity delivered via the physical network.

As in the case of transmission networks, competition for providing the physical infrastructure is naturally limited. Accordingly, access, investments and prices are regulated in a similarly in form to transmission activities.

Trading of electricity is a deregulated activity. It is based on the premise that the end user can freely choose the trading company he buys from. The role of the regulator is to ensure this freedom of choice.

Market operation

Most deregulated markets include central market places where trading between wholesale market participants takes place.
Trading platforms are provided by independent clearing houses. Market participants comprise generators, authorized (large industrial) consumers, and trading entities.

Generators offer energy in the spot market up to 24 hours in advance, and wholesale consumers and trading houses buy based on their demand forecasts. Matching of bids and offers in the spot market happen on a non-bilateral basis. Prices are fixed on an hourly basis at the prevailing marginal price for the specific hour. Complementing the spot market, many deregulated markets have introduced futures markets and the option for participants to trade bilaterally.

System operation

In spite of advances in technology, real-time and short term operational decisions related to the safety of the network are still centralized in the hands of a designated system operator.

The designated system operator also often assumes the role of system planner.

Role of governments

Governments still play an important role in any deregulated market environment.

Regulators design and enforce market rules of the deregulated market as a whole and suggest appropriate changes to improve the system. Moreover, they ensure separation of duties and regulate the monopolistic parts of the system—particularly the physical transmission and distribution networks—with the aim to ensure free access, steer investment decisions and guarantee the adequacy of prices.

Finally, governments define quality and environmental standards. Since the environmental effects of power generation are not fully internalized in the price structures of most markets, governments regularly choose to intervene, for example, to enforce clean air standards or promote the construction of renewables-based generators and the development of revolutionary technologies (see section 2.2.2).
2.2.2 Climate change

In its "Fifth Assessment Report" [22], the Intergovernmental Panel on Climate Change (IPCC) identifies the concentration of atmospheric CO₂ as the main driver of climate change. It attributes the rising concentration of greenhouse gases predominantly to human influence:

"Warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, sea level has risen, and the concentrations of greenhouse gases have increased. [...] Human influence on the climate system is clear. This is evident from the increasing greenhouse gas concentrations in the atmosphere, positive radiative forcing, observed warming, and understanding of the climate system."

The IPCC has defined four scenarios, RCP2.6 to RCP8.5. Table 2.10 gives an overview of the assumed carbon emissions per each scenario and its forecasted effect on global temperature and sea levels.

Limiting a rise in global surface temperature to 2°C over pre-industrial levels has widely been considered as necessary to avoid dangerous consequences from climate change. The IPCC estimates that global surface temperature has increased from 1850 to 2012 by between 0.65°C and 1.06°C. The aggregate of this increase and the estimated further rise in temperature exceed the 2°C threshold under all four scenarios.

Since establishment of the IPCC in 1988, many countries have implemented measures to curb greenhouse gas emissions (see below). However, although 2012 data suggests that the annual increase in total global CO₂ emissions might have slowed down permanently [24], emissions are still on the rise and have more than doubled from 1971 to 2010 (see Figure 2.4). Total CO₂ emissions reached 34.5 gigatons in 2010. This amount represents more than double the upper limit of the assumed average annual emissions under IPCC scenario RCP2.6 and it exceeds the mean of the assumed range of average

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5The four RCP ("Representative Concentration Pathway") scenarios represent a range of potential climate policies, "one mitigation scenario leading to a very low forcing level (RCP2.6), two stabilization scenarios (RCP4.5 and RCP6), and one scenario with very high greenhouse gas emissions (RCP8.5)." [22] The numbers denote the approximate total radiative force in the year 2100 relative to the year 1750 (see [23] for a definition of the term).
annual emissions until 2100 under IPCC scenario RCP4.5. Consequently, it seems almost certain that large-scale emission reduction programs will be required to mitigate climate change.

**The role of electric power generation**

Electric power generation substantially contributes to total CO$_2$ emissions. Emissions grew by 76% from 1990 to 2010, and the sector's share rose to approximately 40% in 2010 (see Figure 2.5).

Regional differences have been dramatic: while the United States increased emissions by 22% and the European OECD members kept emissions flat, China and other countries in Asia increased CO$_2$ emissions from electricity generation dramatically. China's emissions grew by 455% from 1990 to 2010. The country is now the world’s biggest generator of greenhouse gases from electricity generation.$^6$

To better understand the dynamics, total emissions from electricity production can be decomposed into four constituent components (compare for

---

$^6$China is also now the biggest overall contributor to global CO$_2$ emissions from fuel combustion with a share of 24%, followed by the United States with a share of 18%.
Figure 2.4: Global CO$_2$ emissions from fuel combustion [13]

example [25]) as follows:

\[
\text{Total emissions} = \text{Carbon intensity} \times \text{Energy intensity} \\
\times \text{Living standard} \times \text{Population}
\]

\[
= \frac{\text{Total emissions}}{\text{Generation}} \times \frac{\text{Generation}}{\text{GDP}} \\
\times \frac{\text{GDP}}{\text{Population}} \times \text{Population}
\]

The first two factors are indicators of a region’s resource efficiency: \textit{carbon intensity} denotes emissions per unit of electricity output and is an indicator of the quality of the region’s electricity sector; \textit{energy intensity} denotes electricity used per unit of gross domestic product and is an indicator how efficient the region’s industry is with regards to its use of electricity.

The last two factors are indicators of a region’s economic output: \textit{living}
standard denotes the region’s per-head gross domestic product; population denotes the size of its population.

Figures 2.7, 2.8, 2.9, and 2.10 show the development of the four factors from 1990 to 2010 for the United States, Eurasia, China, and Asia excluding China. Table 2.11 shows the relative changes in the four factors from 1990 to 2010, Table 2.12 shows how carbon intensity, energy intensity, and living standard compared relative to those of the European OECD members.

Together, the exhibits illustrate the future opportunities and challenges in reducing global greenhouse gas emissions from electricity generation:

(i) Europe reduced carbon intensity by 26% from 1990 to 2010, and the trajectory of that ratio suggests that further efficiency gains are possible. In comparison, China produced 2.3 times, Asia (excluding China) 1.9 times, and the United States 1.6 times as much CO₂ per unit of generated electricity in 2010. This indicates substantial potential for emission reductions through an increased use of clean energy sources across all four regions.

(ii) A similar observation can be made with regards to energy intensity:
China uses 4.5 times, Asia (excluding China) 1.7 times, and the United States 1.4 times as much electricity per unit of economic output as Europe. This gap can potentially be narrowed by introducing more efficient manufacturing equipment, processes and end-user appliances in the three regions.

(iii) As a strong counter balancing factor, living standards, particularly in China, have been rising dramatically, but are still very low compared to the United States or Europe. Assuming China will continue to grow strongly, the rise in economic output will create a growing demand for electricity.

(iv) Lastly, world population grew substantially from 1990 to 2010 and is predicted to grow further in the coming years. This will create sustained upward pressure on electricity demand and emissions.

(v) On a global scale, the increase in living standards (+30%) and population growth (+30%) clearly dominated carbon intensity (-3%) and energy intensity (+7%) as drivers of total emissions from 1990 to 2010. In order to break that trend in the future, more intense efforts to improve carbon intensity and energy intensity will be required.
Figure 2.7: Carbon intensity (emissions to electricity produced) [13]

Figure 2.8: Energy intensity (electricity consumption to GDP) [13]
Figure 2.9: Living standards (GDP per head) [13]

Figure 2.10: Population [13]
Table 2.11: Total emissions from electricity production – changes in key drivers from 1990 to 2010 (calculated from data provided in [13])

Policy instruments to curb emissions

The above shows that reduction of greenhouse gases from electricity generation can be achieved through a range of very different measures—from consumer demand side management to efficiency improvements of manufacturing processes, to improvement of power production itself. Independent agents influence the outcome of particular measures. This is particularly true in a deregulated power market.

Policy makers are confronted with the challenge of selecting the most effective and efficient set of measures and ensure minimum costs to society. Policy makers typically revert to instruments that can broadly be divided into two categories: market-based instruments and prescriptive instruments.

Market-based instruments aim to influence agents’ behavior by introducing a cost to pollution. Traditionally, producers or consumers of electric power did not incur any costs of greenhouse gases originating from their activities. Market-based instruments internalize the environmental costs to society by introducing a price for emissions. As an effect, emissions reductions become an integral part of agents’ decision making. Most economists believe that this approach incentivizes behavior that results in the most efficient, lowest-cost way to achieve environmental goals. Market-based instruments are typically either volume-based or price-based.

Cap-and-trade schemes are volume-based instruments. A government body sets an upper limit for emissions for a given time period. It then issues
Table 2.12: Key drivers 2010 compared to OECD Europe (calculated from data provided in [13])

<table>
<thead>
<tr>
<th>Region</th>
<th>Carbon intensity</th>
<th>Energy intensity</th>
<th>Living standard</th>
</tr>
</thead>
<tbody>
<tr>
<td>United States</td>
<td>1.60×</td>
<td>1.43×</td>
<td>1.50×</td>
</tr>
<tr>
<td>OECD Europe</td>
<td>1.00×</td>
<td>1.00×</td>
<td>1.00×</td>
</tr>
<tr>
<td>China</td>
<td>2.31×</td>
<td>4.45×</td>
<td>0.11×</td>
</tr>
<tr>
<td>Asia ex China</td>
<td>1.90×</td>
<td>1.73×</td>
<td>0.15×</td>
</tr>
<tr>
<td>World</td>
<td>1.65×</td>
<td>1.80×</td>
<td>0.27×</td>
</tr>
</tbody>
</table>

emission permits to market participants via an auction or free allocation. A single permit allows its holder to release a defined volume, typically a metric ton, of CO₂ during a defined time period into the atmosphere. Permits can be traded between market participants. By introducing a cap below the volume of emissions that would be created in an unconstrained environment, the regulator creates an initial demand for permits. A market participant will be willing to sell a permit in his possession as long as the price of the permit exceeds that participant’s cost to eliminate one additional unit of emissions. Likewise, electricity producers will continue to buy permits as long as the marginal profit from emitting an additional unit of CO₂ exceeds the price of a single permit. Consequently, prices for permits should in theory stabilize at the point where the cost to eliminate one additional unit of emissions equals the benefit from producing one additional unit of emissions. Through that mechanism, cap-and-trade schemes ensure that a defined reduction target is reached in the most cost efficient manner.

An emissions tax is a price-based instrument. By introducing a fixed tax per unit of CO₂ emitted, regulators incentivize emission reductions. In theory, market participants will continue to reduce emissions until the cost of reducing one more unit of emissions exceeds the carbon tax. Other things equal,

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8 This paper focuses on CO₂ emissions. However, it should be noted that cap-and-trade schemes exist for pollutants other than CO₂.

8 Trading is typically organized through regulated markets that create liquidity and facilitate price discovery. These markets are typically open to registered entities outside the power market, and in particular to the financial industry.
carbon efficient producers will gain a competitive advantage over less carbon efficient rivals, which over time creates a carbon efficient market. Variants of emissions taxes exist in the form of energy taxes or carbon taxes, whereby taxes are either be based on the amount of energy produced or on the carbon content of the fuel consumed.

Carbon taxes are widely used to tax transportation fuel, since measuring emissions of individual vehicles would not be practical. In the context of electricity production, emissions taxes have clear advantages over carbon taxes or energy taxes, since the latter two would not discriminate between different efficiency levels or different emissions levels of power stations. This is of particular importance for the development of carbon capture and sequestration (CCS) technologies, which consume slightly more fuel than conventional stations but have the potential to reduce emissions by 90%. Stations with CCS technology would attract higher carbon taxes under non-emissions based tax regimes because of their higher fuel consumption, but they would not receive any benefits from reducing CO₂ emitted into the atmosphere.

Finally, prescriptive instruments, which are also referred to as command-and-control instruments, are defined as legislative measures that directly regulate certain aspects of an activity. This, for example, includes introducing emissions standards, renewable energy quotas, or banning certain technologies.

Most economists argue that market-based instruments, by internalizing the cost of pollutants to society, set better incentives than command-and-control measures to achieve a desired outcome in a cost-efficient way. Command-and-control instruments are often criticized for being too inflexible and inefficient. Technological and market uncertainty, in particular, can impede the long-term effectiveness of rigid prescriptive instruments. However, in certain environments command-and-control instruments can provide a more direct and faster means to steering market participants' behavior than market-based instruments.

It should be noted that this section serves the purpose of laying the foundation for the problem definition introduced in 3 rather than providing full coverage of available policy instruments and their respective advantages and disadvantages. A more comprehensive coverage would need to include instruments such as preferential treatment of certain technologies through subsidies and government-sponsored research, development, demonstration and deployment.
Implementation examples of different policy instruments

The most prominent example of a cap-and-trade scheme is the EU Emissions Trading System. The scheme was launched in 2005 to reduce emissions in 31 participating countries (all 28 EU countries plus Iceland, Norway, and Liechtenstein) and ensure compliance with the reduction goals set by the Kyoto protocol. The scheme exemplifies one of the risks of cap-and-trade instruments. Due to the economic crisis, emissions in the European Union fell below the cap—80% of 1990 levels—introduced for the second trading phase (2008-2012). As a consequence, demand for permits fell dramatically, bringing prices down to virtually zero and eliminating the instrument’s effectiveness in further reducing emissions. The scheme has meanwhile entered the third trading phase, which covers 2013 to 2020 and introduced more restrictive caps and reforms such as the auctioning of permits. The EU Emissions Trading System aims at an 80–95% reduction of greenhouse gases by 2050 compared to 1990 levels.

Tax-based schemes today mostly exist in the form of carbon taxes on transportation fuel. Most developed countries and many developing countries have introduced such taxes.

Command-and-control schemes are the most used instruments today. The "2013 Proposed Carbon Pollution Standard for New Power Plants", issued by the United States Environmental Protection Agency on Sep 20, 2013 [5] provides a recent example. It limits the CO₂ emissions from fossil fuel-fired generators to 1,100lb (0.5 metric tons) per MWh, and thereby effectively bans the construction of new conventional coal-fired generators, which produce emissions of c. 0.8 metric tons of CO₂ per MWh (see 2.1.3). A second example for a ban of a specific technology is the decision of the German government, following the Fukushima nuclear accident, to shut down all nuclear power plants by 2022.

Command-and-control schemes are often based on quotas. The German "Erneuerbare-Energien-Gesetz" (renewable energies law, EEG) provides prominent examples of such rules. It governs that by 2020 the contribution from renewable resources to electric power generation shall increase in 10-year steps to at least 80% by 2050. In addition, the EEG mandates that greenhouse gas emissions shall be reduced by 95% by 2050 against 1990 levels, in line with the goals established by the EU Emissions Trading System.

Finally, command-and-control schemes exist at the end-user level. Many
countries have introduced minimum efficiency standards for electrical appliances such as dishwashers and refrigerators, and fuel efficiency standards for cars.

As is the case for the United States and Europe, China has been using a mixture of market-based instruments and prescriptive instruments. It has introduced a relative emission reduction target, aiming at reducing CO$_2$ emissions per unit of GDP until 2020 by 40–45%, from 2005 levels. The country aims to increase the share of renewable energy sources to 15% by 2020. It has introduced cap-and-trade schemes, similar to the EU Emissions Trading System, in a number of large cities and provinces. In addition, the Chinese government is the largest investor in renewable energies.

Neither the United States nor China have committed to absolute emission reduction targets yet.

2.2.3 Variable energy resources

In light of the serious damage to global climate caused by greenhouse gases, countries around the world have made strong commitments to increase the use of renewable resources as an important component of their national energy policy.

Germany, as an example, has increased the contribution from renewable sources to electricity generation to 23% in 2012 and has committed to increase that ratio to 80% by 2050. As of 2012, more than 53% of generation from renewables in Germany came from wind and solar.

Like Germany, most countries with significant commitments to renewables will depend heavily on variable energy resources (VER) such as wind and solar, to meet their respective targets. This has created new challenges for grid operators [26].

Characteristics of variable energy resources

In contrast to conventional generating technologies, electricity generation from wind and solar presents the following challenges:

(i) Both output from wind and solar are highly variable. In some areas, wind output is negatively correlated with demand, with average output being at its highest during the night, when demand is at its lowest. Fluctuations
in output are typically much higher than fluctuations in demand during the same period. Output from individual photovoltaic plants is similarly variable and can drop by up to 90% under cloud cover. However, solar output is often positively correlated with demand, often reaching peak output a few hours before demand peaks.  

(ii) Both wind and solar output are difficult to predict at the time of day-ahead unit commitment. Although greatly reduced in recent years, the average error of day-ahead wind forecasts is still between 15% and 30%, compared to an average day-ahead forecasting error of less than 1% for demand. Such forecasting errors can have severe consequences particularly during extreme weather conditions ("ramp events"), when output particularly from wind turbines can change dramatically, often within minutes.

![Graph showing demand and wind variability](image)

Figure 2.11: Demand and wind variability based on a hypothetical capacity mix for the ERCOT region (simulated from data provided in [14])

(iii) Ideal locations for wind and solar generators are often remote from
Figure 2.12: Demand and solar variability based on a hypothetical capacity mix for the ERCOT region (simulated from data provided in [14])

Figure 2.13: Contribution from wind (year) based on a hypothetical capacity mix for the ERCOT region (simulated from data provided in [14])
major centers of consumption, calling for investments in new transmission infrastructure.

Responses to the challenges posed by variable energy resource generators

The characteristics of power generation from VER’s present major challenges to grid operators once the contribution from VER’s becomes significant. In particular, operators need to counter the increased output variability and uncertainty.

While a number of potential responses exist, the most effective counter measure in most environments today is to increase the operating reserve consisting of conventional generators that can be started up quickly to balance a drop in output from VER’s. In general, this translates into higher nominal generating capacity and consequently higher costs from generation for a given region.

However, a number of additional actions have the potential to mitigate the
negative effects from introducing more VER's into an energy mix in the future:

(i) Output forecasts heavily depend on the quality of weather forecasts. Weather forecasts have significantly improved with respect to accuracy, spatial granularity, and measurement frequency. Further improvements will potentially further reduce output forecast errors.

(ii) Since forecast accuracy decreases with the length of the forecast, more frequent unit commitment decisions, comprising shorter gate-closure periods, shorter commitment periods, and a layering of real-time decisions on top of day-ahead planning, can help to reduce forecasting error and therefore the size of the operating reserve.

(iii) While output from individual wind and solar generators can fluctuate strongly, a geographically diversified portfolio will deliver a more balanced output because of the differences in weather conditions across locations. This effect can be exploited by interconnecting formerly unconnected regions, thereby creating larger balancing areas.

(iv) The capacity of a fleet of conventional generators to balance the output variability from VER's can be increased both by technical upgrades of individual intermediate and base load plants and by adding a higher proportion of peak load units to the fleet of generators.

(v) Hydroelectric generation can provide a natural balance, since output from hydro sources can be ramped up very quickly. However, hydro capacity is limited and new construction constrained by environmental limitations.

(vi) The deployment of smart metering technology will allow for an introduction of dynamic pricing schemes for retail customers. Rising prices during peak demand hours would provide a strong incentive for households to reduce consumption (demand response) when generation resources are scarce.

(vii) Energy storage capabilities can buffer the variability of electricity output from VER generators. Storage technologies include pumped hydro storage, compressed air energy storage and batteries. However, pumped hydro storage to date is the only mature, price competitive technology available, and scalability is not sufficient to react to the expected increase in VER generators in most countries.
2.2.4 Shale gas exploration

A report by the Massachusetts Institute of Technology on "The Future of Natural Gas" [27] states that remaining resources of natural gas in the United States have grown by 77% since 1990, in spite of ongoing exploitation. This development is mainly driven by the discovery of large shale gas resources in many parts of the United States, and advances in hydraulic fracturing ("fracking") that have made exploration and exploitation of these resources economically attractive. The industrial-scale exploitation of shale gas has fundamentally changed the power generation landscape in the United States. In 2012, natural gas production in the United States accounted for 19.8% of global production, making the country the world's largest producer.

While the United States and Canada are today the only two countries that explore unconventional natural gas on an industrial scale, the U.S. Energy Information Agency estimates that technically recoverable shale gas resources amount to a total of 7,299 trillion cubic feet worldwide - more than ten times the estimated volume in the U.S. (665 trillion cubic feet)\(^{10}\). This adds considerably to the 15,583 trillion cubic feet of unproven technically recoverable conventional gas resources. Consequently, natural gas will most likely play a very prominent role as energy source in the future.

**Characteristics of natural gas**

Natural gas compares favorably to coal and oil in many aspects:

(i) Natural gas is the fossil fuel with the lowest carbon content. A modern combined cycle gas-fueled generator produces 342 kg/MWh of CO\(_2\), compared to 823 kg/MWh of CO\(_2\) generated by a modern coal-fueled generator (see appendix A). This provides a cost efficient means to substantially reduce carbon emissions from electric power generation.

(ii) Natural gas is a highly flexible fossil fuel. Beyond electricity generation, it is used in many industrial processes and for residential and commercial heating. The Massachusetts Institute of Technology forecasts that in addition, natural gas will increasingly be used as a transportation fuel in the future, reducing the United States’ dependence on oil imports [27].

\(^{10}\)The top 10 countries are (exploitable shale gas resources in trillion cubic feet in brackets): China (1,115), Argentina (802), Algeria (707), United States (665), Canada (573), Mexico (545), Australia (437), South Africa (390), Russia (285), and Brazil (245)[28].
(iii) Gas-based power generators have much shorter start-up times than coal- or nuclear-based generators. This makes them a crucial source of backup power to power grids with a large share of variable energy resources.

That said, natural gas has also some major disadvantages over other fossil fuels and renewable energy resources:

(i) Due to its physical form, transportation of gas depends on the existence of pipelines, liquification facilities, and specialized transportation vessels. The cost of developing and maintaining such an infrastructure represents a large fraction of overall supply chain costs. This has impeded the development of international markets. Virtually all of the natural gas production in the United States, for example, is being used domestically, and global exports represented only 24% of global production in 2012. This has led to local gas markets with large price differences across countries (see below) and even across different regions of a country.

(ii) While cleaner than other fossil fuels, natural gas still contains substantial amounts of carbon. Accordingly, its ongoing use as an energy source depends on the extent of potential national greenhouse gas reduction measures.

Natural gas prices

Figure 2.15 gives an overview of the development of natural gas prices in five different countries. It shows how the shale gas revolution in the United States has led to a dramatic drop in prices from a peak near $9 per MMBtu in 2008 to less than $3 per MMBtu in 2012. During the same period, prices in import markets such as Germany and the United Kingdom have returned—after a recession-driven decline in 2009 and 2010—to 2008 levels between $9 and $11 per MMBtu.

The decline in prices in the United States has created a situation where combined cycle gas-fired plants compete with coal-fired plants and nuclear plants as base load technology. As a consequence, large investments in recent years have flown into the construction of gas-based generating capacity while almost no capital has been invested in new coal-based or nuclear-based power stations.

11 The largest exporter of natural gas is the Russian Federation. It exported 185 billion cubic meters in 2012, representing 28% of its 2012 production (681 billion cubic meters) [17].
Although shale gas production in the United States is still increasing, guaranteeing abundant supply of natural gas in the short term, the development of international markets, a large-scale retirement of coal plants, or an increased use of natural gas in transportation could lead to a supply shortage in the medium and long term\textsuperscript{12} and higher prices.

This would put an energy strategy at risk that relies too heavily on natural gas.

![Natural gas prices in different regional markets](image)

Figure 2.15: Natural gas prices in different regional markets [29]

\textsuperscript{12}[27] estimates that under some scenarios the United States might import up to 50% of the natural gas used domestically by 2050.
Chapter 3

Problem definition

3.1 High-level problem definition

The research presented in the following chapters focuses on capacity expansion under uncertainty. Scenarios are introduced that increase uncertainty with regards to regulatory actions and market parameters in a stepwise approach. At each step, optimization techniques are used to find a cost-optimal capacity expansion strategy. Results are then compared with respect to energy mix and total cost.

The model assumes a central planning process in three consecutive steps. Capacity expansion decisions are taken at the beginning of years 1, 11, and 21. Capacity after expansion needs to be sufficient to satisfy peak demand during the respective upcoming period. The overall planning horizon is 50 years.

Generating technologies available for capacity expansion include four fossil fuel-based (coal, coal CCS, combined cycle gas turbines, single-cycle gas turbines), one nuclear-based, and two renewable-based (onshore wind, photovoltaic solar) technologies.

It is assumed that a legacy portfolio exists at the start of the planning horizon that is sufficiently large to satisfy an initial demand profile. The legacy portfolio is being retired in three steps of 1/3 of its initial capacity during years 1 to 10, 11 to 20, and 21 to 30, respectively. As a consequence, the legacy portfolio has been fully replaced by new investments after 30
Demand grows by a fixed rate of 2% annually over the first 30 years and stays constant thereafter. Accordingly, capacity expansion needs to be sufficient to both replace retired assets and build additional net capacity to satisfy demand growth.

It is assumed that cumulative carbon emissions over the 50-year horizon are constrained by a fixed cap. The cap is introduced either at the beginning of year 1, year 11, year 21, or only at the end of year 50, reflecting current regulatory uncertainty. A penalty is then imposed at the end of year 50 whenever the cumulative carbon stock exceeds the cap. The penalty is calculated as the product of the excess volume of CO₂ measured in tons and a fixed rate per ton.

Market uncertainty is introduced in the form of variable prices for natural gas and variable construction costs for three developing technologies: coal CCS, wind, and solar.

The discounted total cost of a certain energy mix comprises capital cost, fixed annual cost for operating and maintenance (O&M), variable O&M cost, and a potential emissions penalty.
3.2 The Electric Reliability Council of Texas (ERCOT)

The transmission network of the United States is divided into three interconnected transmission networks: the Western Interconnection, the Eastern Interconnection, and the Electric Reliability Council of Texas (ERCOT) (see Figure 3.1). Although some physical connections between the three networks exist, the capacity of these lines is so low that all three areas can be considered isolated from each other.

![NERC Interconnections Diagram](Image)

Figure 3.1: Interconnections of the North American electric grid [30]

Due to the availability of high-quality data, the comparatively homogeneous geographical conditions, and its good potential for renewable power generation, the ERCOT region was chosen to provide the baseline for this research.

ERCOT is the independent system operator for Texas. It services 23 million customers and produces 85% of the state’s electricity demand. In addition to its role as system operator, ERCOT also provides the wholesale trading platform and acts as a clearing house.
ERCOT manages more than 77,000 MW of nominal capacity distributed across 550 generating units in 2012. 56% of generation capacity is provided by gas-powered generators. With 10,033 MW of nominal capacity, ERCOT also managed the largest installed base of wind turbines of all states in the United States in 2012 (see Table 3.1).

<table>
<thead>
<tr>
<th>Source</th>
<th>Nominal capacity 2012 (MW)</th>
<th>Share of nominal capacity 2012</th>
<th>Share of total generation 2012</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>5,150</td>
<td>7%</td>
<td>12%</td>
</tr>
<tr>
<td>Coal</td>
<td>18,215</td>
<td>24%</td>
<td>34%</td>
</tr>
<tr>
<td>Natural gas</td>
<td>42,945</td>
<td>56%</td>
<td>45%</td>
</tr>
<tr>
<td>Wind</td>
<td>10,033</td>
<td>13%</td>
<td>9%</td>
</tr>
<tr>
<td>Other</td>
<td>868</td>
<td>1%</td>
<td>0%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>77,211</strong></td>
<td><strong>100%</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

Table 3.1: Energy mix for the ERCOT region, 2012 [14]

Further ERCOT input data include (i) the total hourly demand in 2012, (ii) the total hourly output from the installed fleet of wind turbines in 2012, and (iii) the total hourly output from the installed photovoltaic panels in 2012 (for further information see sections 3.3.2 and 3.3.6).

### 3.3 Detailed model description

#### 3.3.1 Included generating technologies

Table 3.2 documents the generating technologies included in the model. For further detail see appendix A.

The rationale for this selection is as follows:

(i) Two different coal-fired technologies—advanced pulverized coal and advanced pulverized coal with carbon capture and sequestration (CCS)—represent both the most efficient technology available today and the anticipated most advanced potential technology for the future.
<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital cost (M$ per MW)</th>
<th>Fixed cost (M$ per MW-year)</th>
<th>Variable cost ($ per MWh)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear dual unit</td>
<td>5.5</td>
<td>0.093</td>
<td>4.2</td>
<td>-</td>
</tr>
<tr>
<td>Advanced pulverized coal generation</td>
<td>3.2</td>
<td>0.038</td>
<td>21.9</td>
<td>0.823</td>
</tr>
<tr>
<td>Advanced pulverized coal generation with carbon capture and sequestration</td>
<td>5.2</td>
<td>0.081</td>
<td>33.3</td>
<td>0.112</td>
</tr>
<tr>
<td>Advanced combined cycle turbine</td>
<td>1.0</td>
<td>0.015</td>
<td>29.0</td>
<td>0.342</td>
</tr>
<tr>
<td>Advanced combustion turbine</td>
<td>0.7</td>
<td>0.007</td>
<td>49.4</td>
<td>0.518</td>
</tr>
<tr>
<td>Onshore wind</td>
<td>2.2</td>
<td>0.040</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Solar photovoltaic</td>
<td>3.9</td>
<td>0.025</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3.2: Key parameters for the included technologies [16]

(ii) Two gas-fired technologies—an advanced single-cycle combustion turbine station and an advanced combined-cycle station—represent the typical peak demand technology and the base/intermediate technology with the largest share in the current ERCOT energy mix, respectively.

(iii) One type of nuclear generator was included.

(iv) A 100 MW onshore wind farm and a 150 MW photovoltaic installation represent generation from variable energy resources.

This portfolio of choices covers the major components of ERCOT’s energy mix, and with the exception of hydroelectric power generation—also that of a typical developed country well. Hydroelectric power generation was not included due to Texas’ very limited potential for hydro.

### 3.3.2 Demand

Figure 3.2 shows the hourly demand data set, reflecting hourly load in the ERCOT region in 2012, sorted by hour of the year. The data set was rearranged as a load profile and then partitioned into 10 load blocks, as shown
The load blocks were generated in two steps: in the first step, a "super load block", comprising the top 20 peak hours, was created; in the second step, the demand range of the remaining 8740 hours was cut in nine equidistant blocks. The "super load block" denotes an average demand of 65,204 MW. This compares to an actual demand of 65,805 MW during the peak hour of the year.

Modeling of demand growth

Demand is modeled as a deterministic quantity as shown in Figure 3.4. It is assumed that demand grows under all scenarios by 2% annually during the first 30 years. This is slightly higher than the compound annual growth in the United States from 1990 to 2010 (+1.5%) to account, for example, for new consumers such as electric vehicles or electric heating. However, it should be noted that actual growth rates will very likely deviate considerably from the assumed growth rate, and that the arguments developed in this paper would stay in most parts valid under different growth patterns.
Figure 3.3: Load profile, based on hourly demand, ERCOT region, 2012 [14]

Figure 3.4: Assumed demand growth (model parameter)
After year 31, demand is assumed to be constant. This choice is technically driven and eventually follows from the treatment of capital cost in the objective function: overnight capital costs related to the construction of a power station are transformed into an annuity spanning the useful lifetime of the respective asset (30 years for all technologies). To ensure that technologies of different capital intensity are treated equally, it is crucial that all generating assets are included with their full annuity in the objective function. Thereby, the simulation horizon extends 30 years beyond the last build decision (the beginning of year 21). No demand growth is assumed beyond year 30 to ensure that all the investment decisions are approximately of the same size.

For any given year, hourly demand and the load profile are derived by scaling up the initial demand pattern $d_0$ by the cumulative growth up to the respective year.

\[
\text{demand}_{\text{year},\text{hour}} = d_{0,\text{hour}} \cdot (1 + \text{growth}_{\text{year}})_{\text{hour}}^{\text{year}-1} \prod_{y' = 1} \left(1 + \text{growth}_{y'}\right)
\]

### 3.3.3 Regulatory uncertainty

Regulatory uncertainty exists in the form of a potential limitation on cumulative CO$_2$ emissions (the cap). The cap is introduced at some future point during the 50-year time horizon. Whenever a capacity expansion strategy leads to a breach of that cap, a penalty is imposed on the difference between the CO$_2$ emissions produced over the 50-year simulation horizon and the cap.

The unconstrained carbon cap serves as a reference point: An initial simulation run is performed for a given growth scenario in absence of any cap. The result of the simulation is a cost-optimized expansion strategy. That strategy produces a deterministic volume of cumulative CO$_2$ emissions. This volume defines the unconstrained carbon cap$^\dagger$.

$^\dagger$For the standard scenario with 2% annual demand growth during the first 30 years and no growth thereafter, and with deterministic gas prices and capital costs, the unconstrained carbon cap is 9.3 billion metric tons.
A cap can be introduced at four different introduction times: (i) at the beginning of year 1 and prior to any capacity expansion decision; (ii) at the end of year 10, prior to the second capacity expansion decision; (iii) at the end of year 20, prior to the third capacity expansion decision; (iv) at the end of year 50, after all capacity expansion decisions.

The value of the cap can take five discrete values if introduced at the beginning of year 1: 20%, 40%, 60%, 80%, or 100% of the unconstrained cap. For all other introduction times, the cap is modeled as a normally distributed random walk without drift, starting at 60% of the unconstrained cap. The random walk is limited at 20% and 100% of the unconstrained cap, respectively.

In scenarios where the cap is introduced at the end of years 20 or 50, the interim state of the random walk (after year 10 or after years 10 and 20, respectively) serves as model input. This reflects interim guidance given by regulators or research institutes. The information is of particular value whenever the interim state deviates considerably from the starting point. Figure 3.5 illustrates this: random walks with larger (non-restrictive) interim carbon caps (blue paths) will unlikely produce a restrictive final cap, and vice versa (red paths). This information can be exploited by the model to make better investment decisions.

For each simulation sample, the cumulative CO₂ emissions at the end of the 50-year horizon are compared with the carbon cap of that sample. A linear penalty is applied whenever the cumulative emissions exceed the cap.

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\(^2\)As a motivation of the expected value of 60% and the limits of 20% and 100%, consider the scenarios defined by the International Panel for Climate Change in its recent report (see section 2.2.2): (i) In a business-as-usual environment with no emission reduction measures, the average increase in demand over the 50-year time horizon, given a 2% annual demand growth during the first 30 years, from initial levels would result in average emissions of 1.55 times the initial volume of emissions. Assuming total global emissions-34.5 gigatons in 2010-would increase in lockstep with this development, the resulting average global emissions would equal 34.5% = 53.5 gigatons. This amount would exceed the upper limit of the "stabilizing" scenario RCP6.0 and would be slightly lower than the lower limit of the worst-case scenario RCP8.5. (ii) Cutting the elevated baseline to 60% would result in 1.55 × 60% = 93% of initial emissions. Assuming total global CO₂ emissions were to grow proportionately, the resulting average annual volume would be 34.5 × 60% = 32.1 gigatons. This would correspond with the mid-point of emissions assumed for the "stabilizing" scenario RCP4.5. (iii) Finally, a cap of 20% of the unconstrained cap would result in 1.55 × 20% = 32% of initial emissions, and a proportionate reduction of total global emissions would result in an average annual value of 34.5 × 32% = 10.7 gigatons. This amount equals the mid-value of the best-case, "mitigating" scenario RCP2.6.
The retrospective penalty formula which includes the emissions generated prior to a cap’s introduction date is motivated by the concept of fully internalizing the social cost of emissions: Given the long residence time of atmospheric CO₂, damage from climate change is assumed to be a function of the cumulative emissions generated over the 50-year horizon. Therefore, it is realistic to assume that the cap at the time of its introduction reflects the cumulative emissions generated up to that point, potentially by reducing the cap by that amount. While the penalty formula in such a scenario would then only apply to future emissions, the ex-ante reduction of the cap represents a de-facto extension of the penalty formula across the full 50-year horizon.

3 A penalty of $50,000 per ton of CO₂ was set for all worlds as a highly restrictive barrier to discourage capacity expansion strategies that trade lower capital cost and operating expenses against a penalty.
3.3.4 Market uncertainty 1 – price of natural gas

Due to the dramatic growth in shale gas exploration, the price for natural gas has been declining strongly in recent years both in the United States and Canada (see section 2.2.4). As an effect, modern combined-cycle gas generators have become a viable base load technology, and new capacity in the United States has almost exclusively been added in the form of gas generators or wind turbines.

Gas markets have not developed into global markets due to the cost of transportation and the lack of adequate transportation infrastructure. Global prices therefore vary significantly with countries relying on imports experiencing much higher prices than the United States. Japan and Korea are among the most expensive markets with recent landed prices exceeding $15/MMBtu (see [29]).

Under the assumptions that (i) the market for natural gas will over time develop into a global market, (ii) demand for natural gas in the United States increases strongly due to the ongoing changes in the country’s energy mix (see [27]), many industry experts are considering scenarios of higher gas prices in the future.

In order to better understand the effect of uncertain gas prices on the optimal capacity expansion strategy, gas prices are modeled as either (i) fixed at $4/MMBtu, or (ii) following a random walk.

The random walk is log normal with an annual drift of 1.0211 and a standard deviation of 0.084. This yields an expected value of $4/MMBtu \times 1.0211^{50} = $11.36/MMBtu after 50 years. Figure 3.6 shows a set of 100 samples with yearly means, 10% percentiles, and 90% percentiles.

3.3.5 Market uncertainty 2 – capital costs of emerging technologies

In its "Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants" [16], the United States Energy Information Agency (EIA) compares the overnight capital cost estimate of the covered technologies with the respective estimates of the preceding report which was published in November 2010, 2.5 years before the current version.

\footnote{These parameters were chosen such that the generated distribution mirrors recent gas price forecasts of the United States Energy Information Agency.}
Table 3.3 shows the estimates for the technologies included in the model. The table reveals significant differences across technologies with respect to cost trajectories:

(i) The established technologies—nuclear, coal and combined-cycle gas and single-cycle gas—remained virtually unchanged.

(ii) The cost estimate for wind and solar PV dropped significantly. The installed base of both technologies has grown rapidly and is expected to continue on a similar path in the next years.

(iii) The cost estimate for coal CCS remained almost unchanged at 61% above those of a conventional coal station of the same size. Although power generation based on coal CCS relies on components that are classified as "revolutionary" by the EIA, no utility-size plant has been built so far, and opportunities for cost reductions have therefore been limited. However, significant cost reductions are expected as a consequence of capacity expansion in that technology in the future.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear dual unit</td>
<td>5,546</td>
<td>5,530</td>
<td>±0%</td>
</tr>
<tr>
<td>Advanced pulverized coal generation</td>
<td>3,292</td>
<td>3,246</td>
<td>-1%</td>
</tr>
<tr>
<td>Advanced pulverized coal generation with carbon capture and sequestration</td>
<td>5,300</td>
<td>5,227</td>
<td>-1%</td>
</tr>
<tr>
<td>Advanced combined cycle</td>
<td>1,043</td>
<td>1,023</td>
<td>-2%</td>
</tr>
<tr>
<td>Advanced combustion turbine</td>
<td>691</td>
<td>676</td>
<td>-2%</td>
</tr>
<tr>
<td>Onshore wind</td>
<td>2,534</td>
<td>2,213</td>
<td>-13%</td>
</tr>
<tr>
<td>Solar photovoltaic</td>
<td>4,943</td>
<td>3,873</td>
<td>-22%</td>
</tr>
</tbody>
</table>

Table 3.3: Overnight capital cost

Modeling capital costs

To account for the differences between established and emerging technologies, the capital cost of both are modeled differently:

Emerging technologies are modeled as variable, following a one-factor learning curve with a random component as overlay: (i) With every doubling of the installed base, capital costs for wind, solar, and coal CCS fall by 20%; (ii) a log normal random walk with zero drift and a standard deviation of 5% over the 50-year lifetime is added as a random element; (iii) capital costs for all three technologies are capped at 100% of their initial value; (iv) the cost for a coal CCS station cannot fall below the cost of a conventional coal generator of the same size; (v) the costs for wind and solar cannot fall below 50% of their respective initial values; (vi) to provide a starting point for a technological learning curve for coal CCS, it is assumed that the legacy portfolio (see section 3.3.7) includes one 650MW demonstration plant.

The capital costs for established technologies are assumed constant.

Figure 3.7 shows the development of capital costs for coal CCS under two capacity expansion scenarios and assuming a 20% learning curve: (i) under the first scenario, 3 coal CCS plants were added in period 1 and none in later periods; this represents a growth of the installed base by a factor of 4,
which results in a reduction in capital cost of \( \log_2(4) \times 20\% = 40\% \) (shown to impact costs immediately after the investment decision); (ii) under the second scenario, the installed base was expanded by one plant each in periods 1 and 3, representing cumulative growth by a factor of 2 and 3, respectively; this resulted in cumulative cost reductions of \( \log_2(2)\% = 20\% \) and \( \log_2(3) \times 20\% = 32\% \), shown immediately after the two investment decisions. Intra-period fluctuations result from the build-independent random walk overlay of 5\% (standard deviation) per year.

![Capital cost (annuity) for coal CCS under capacity expansion strategy](image)

Figure 3.7: Simulated annualized capital cost for a coal CCS station under two different expansion strategies (model output)

**Discussion of model and parameter choices**

By assuming a technological learning curve, the decreasing costs of emerging technologies can be modeled as a direct outcome of a chosen capacity expansion strategy. The model is thus better suited than a model with constant prices to incorporate the future benefits of emerging technologies. In particular, the model is able to test the effectiveness of potential regulatory investment incentives on the long-term attractiveness of a particular technology.
It should be noted though that the cost model used here implicitly assumes that the relative changes in the installed base in the simulated area (in this case ERCOT) closely mirror those of the installed base that underlies the technological learning effect (manufacturers and construction companies typically operate globally).

Table 3.4 motivates the value of 20% chosen as the parameters for technological learning\(^5\): based on actual growth of the installed bases, actual cost reductions for wind and solar over 2.5 years can be explained well by cost reductions from technological learning of between 15% and 25%.

Recent cost reductions in both technologies suggest that further reductions can be expected. However, finding a sound basis for estimating the maximum extend of future cost savings for evolving technologies is not straightforward. The limits for potential cost savings (50% of the initial values for wind and solar) were therefore chosen conservatively, yet large enough to show that incorporating technological learning in a capacity expansion model will result in significantly different results.

### 3.3.6 Output from wind and solar

Figure 3.8 shows the actual output of all wind turbines in the ERCOT region in 2012 as a fraction of installed nominal capacity. This output profile was sorted by demand load block via a 1:1 allocation per hour. The result is shown in Figure 3.9. It illustrates the negative correlation between demand and wind output: when demand is highest (usually during a midday heat), average wind output is lowest.

Figure 3.10 shows the actual output of all photovoltaic capacity in the ERCOT region in 2012 as a fraction of installed nominal capacity. As in the case of wind output, solar output was averaged over the defined demand load blocks. The result is shown in Figure 3.11. In contrast to the pattern for wind, solar output is positively correlated with load. This is expected, since both demand peaks and solar output peaks are usually driven by midday sun (air-conditioning is driving demand).

Relative output levels are assumed to stay constant over the 50-year time horizon.

---

\(^5\)Scenarios with 0% technological learning are included to show the effect of excluding technological learning on capacity expansion strategy.
Figure 3.8: Hourly relative wind output, ERCOT region, 2012 [14]

Figure 3.9: Relative wind output per load block, ERCOT region, 2012 [14]
Figure 3.10: Hourly relative solar output, ERCOT region, 2012 [14]

Figure 3.11: Relative solar output per load block, ERCOT region, 2012 [14]
<table>
<thead>
<tr>
<th></th>
<th>Wind Onshore</th>
<th>Solar Photovoltaic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Installed base (MW)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>158,975</td>
<td>23,605</td>
</tr>
<tr>
<td>2010</td>
<td>198,001</td>
<td>40,670</td>
</tr>
<tr>
<td>2011</td>
<td>238,050</td>
<td>71,061</td>
</tr>
<tr>
<td>2012</td>
<td>282,587</td>
<td>102,156</td>
</tr>
<tr>
<td>Compound growth</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1yr (11–12)</td>
<td>×1.19</td>
<td>×1.44</td>
</tr>
<tr>
<td>2yr (10–12)</td>
<td>×1.43</td>
<td>×2.51</td>
</tr>
<tr>
<td>3yr (09–12)</td>
<td>×1.78</td>
<td>×4.33</td>
</tr>
<tr>
<td>Theoretical cost reduction at 20% learning</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2yr (10–12)</td>
<td>-10%</td>
<td>-27%</td>
</tr>
<tr>
<td>3yr (09–12)</td>
<td>-17%</td>
<td>-42%</td>
</tr>
<tr>
<td>Theoretical cost reduction at 10% learning</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2yr (10–12)</td>
<td>-5%</td>
<td>-13%</td>
</tr>
<tr>
<td>3yr (09–12)</td>
<td>-8%</td>
<td>-21%</td>
</tr>
<tr>
<td>Actual cost reduction</td>
<td>2.5yr</td>
<td>-13%</td>
</tr>
</tbody>
</table>

Table 3.4: Implied learning

3.3.7 Legacy portfolio

The legacy portfolio describes the energy mix present at the beginning of the simulation. It was constructed using two different data sources: (i) the "Report on the Capacity, Demand, and Reserves in the ERCOT Region, December 2012" [31], and (ii) the 15-minute recordings of output per technology during 2012. The data from the two files was combined in the following way:

(i) The nominal capacities for nuclear, coal, wind and solar were derived from the capacity report.

(ii) The nominal capacities for combined-cycle and single-cycle gas generators were derived from the output file, assuming that capacity equals the maximum output from these technologies during 2012.6

(iii) It was assumed that one 650 MW coal CCS demonstration plant ex-

---

6 The capacity report does not differentiate between different gas-fueled generator types.
(iv) It was assumed that one third of the initial capacity per technology is retired during years 1 to 10, 11 to 20, and 21 to 30, respectively.

This results in the energy mix and retirement schedule presented in Table 3.5.

<table>
<thead>
<tr>
<th>Technology</th>
<th>$t_0$ (MW)</th>
<th>Period 1 (years 1-10)</th>
<th>Period 2 (years 11-20)</th>
<th>Period 3 (years 21-50)</th>
<th>Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nuclear</td>
<td>5,150</td>
<td>3,433</td>
<td>1,717</td>
<td>-</td>
<td>6.7%</td>
</tr>
<tr>
<td>Coal</td>
<td>18,215</td>
<td>12,143</td>
<td>6,072</td>
<td>-</td>
<td>23.7%</td>
</tr>
<tr>
<td>Coal CCS</td>
<td>650</td>
<td>433</td>
<td>217</td>
<td>-</td>
<td>0.8%</td>
</tr>
<tr>
<td>Gas CC</td>
<td>26,154</td>
<td>17,436</td>
<td>8,718</td>
<td>-</td>
<td>34.0%</td>
</tr>
<tr>
<td>Gas CT</td>
<td>16,597</td>
<td>11,065</td>
<td>5,532</td>
<td>-</td>
<td>21.6%</td>
</tr>
<tr>
<td>Wind</td>
<td>10,033</td>
<td>6,689</td>
<td>3,345</td>
<td>-</td>
<td>13.1%</td>
</tr>
<tr>
<td>Solar</td>
<td>74</td>
<td>49</td>
<td>25</td>
<td>-</td>
<td>0.1%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>76,873</strong></td>
<td><strong>51,249</strong></td>
<td><strong>25,624</strong></td>
<td>-</td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

Table 3.5: Structure of legacy portfolio and retirement schedule

3.3.8 Decision making

Investment decisions are taken at three points during the 50-year simulation horizon: at the beginning of years 1, 11, and 21.

A decision consists of a build decision and a dispatch strategy.

The build decision governs how many plants per technology are to be built during the succeeding period. It is assumed that new capacity comes online in yearly steps throughout the period to match yearly demand growth.

The amount of newly built capacity is calibrated such that (i) demand can be satisfied at any time during the entire period succeeding a particular decision, (ii) no unnecessary capacity is generated.

---

See section 3.3.5.
The dispatch strategy is expressed as a parameter between 0 and 1. It denotes how the goals of cost optimization and emissions optimization are to be weighted during the yearly economic dispatch decisions. A value of 0 denotes a pure cost optimization, a value of 1 a pure emissions optimization, and a value between 0 and 1 leads to a solution that balances cost optimization and emissions optimization (for further detail see section 3.5.11).

### 3.3.9 Economic dispatch

The economic dispatch process is responsible for satisfying demand in a given year for any given load block during that year. The economic dispatch is solved using linear programming formulation.

The economic dispatch can be optimized for either cost or emissions, or a combination of both goals. The weighting (the "dispatch strategy") is expressed as a parameter $dp$ that can take values between 0 and 1.

(i) For $dp = 0$, the dispatch algorithm will return a solution that is purely optimized for cost.

(ii) For $dp = 1$, the dispatch algorithm will return a solution that is purely optimized for emissions.

(iii) For $0 < dp < 1$, the dispatch algorithm will optimize in three steps: during the first step, a cost optimized solution will be calculated and the resulting level of emissions $em_1$ will be recorded; during a second step, an emissions optimized solution will be calculated and the resulting level of emissions $em_2$ will be recorded; during the third and final step, a weighted average $em_{constraint} = (1 - dp) \times em_1 + dp \times em_2$ is set as an additional constraint of the linear program and a cost optimized solution is calculated which satisfies this additional constraint.

The dispatch strategy provides the model with an additional instrument to control emissions, beyond the main instrument of controlling the technology mix via the capacity expansion process. With significant additional flexibility to react to the final stage of and intermediate information on the emissions cap (see section 3.3.3 for detail): in addition to adjusting the incremental build at each decision stage, the solver can influence the emissions generated by the entire capacity via the dispatch parameter.
3.3.10 Cost function

The model solution is a cost optimized capacity expansion strategy under uncertainty.

Costs are represented as the sum of the net present values (NPV) of four cost components: capital cost, fixed annual operating & maintenance cost, variable operating & maintenance cost, and a potential penalty for breaching the cumulative emissions cap:

\[
NPV_{\text{total cost}} = NPV_{\text{capital cost}} + NPV_{\text{fixed annual o&m cost}} + NPV_{\text{variable o&m cost}} + NPV_{\text{emissions penalty}}
\]

*Capital costs* originate from the construction of new generators. Typically, capital costs are denoted as an "overnight" cost item. To avoid unwanted distortions between technologies of different capital intensity, the one-off payment is translated into an annuity which stretches the useful lifetime of the respective technology. As described in section 3.3.5, capital costs for emerging technologies are modeled as variable under some scenarios. Accordingly, different "vintages" (built during different decision times) of capacity attract different capital costs.

*Fixed operating & maintenance costs* are accounted for as an annual technology-specific cost. Fixed O&M are assumed to stay constant per technology throughout the 50-year simulation horizon.

*Variable operating & maintenance costs* are only incurred per hour of dispatched capacity. Variable operating & maintenance costs comprise both fuel costs and non-fuel O&M expenses. The price for natural gas is modeled as uncertain in some scenarios (see section 3.3.4). Accordingly, O&M costs fluctuate from year to year.

An *emissions penalty* is incurred if by the end of the 50-year horizon, generated cumulative emission exceed the cap imposed by the regulator (see section 3.3.3).

All costs are represented as net present values discounted by a rate of 10%. Costs and discount rate are assumed to be real (no inflation) and pre-tax.
It should be noted, that for those scenarios that include regulatory and/or market uncertainty, cost optimization will be performed on an expected value basis.

### 3.4 Scenario overview

The arguments are being developed over the course of six sections, each supported by the results of section-specific scenarios.

The first section analyses five deterministic scenarios, where no market uncertainty exists and a carbon cap at levels of 20 - 100% of the unconstraining limit is introduced at $t_0$ (scenario group DET – see Table 3.6).

The deterministic cases serve as a reference for subsequent scenarios with uncertainty. They also build the basis to evaluate the cost of ignoring uncertainty and the cost of regulatory uncertainty.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>fixed 20%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D40</td>
<td>fixed 40%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D60</td>
<td>fixed 60%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D80</td>
<td>fixed 80%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D100</td>
<td>fixed 100%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
</tbody>
</table>

Table 3.6: Deterministic scenarios (DET)

The second section introduces regulatory uncertainty. The carbon cap is the result of a random walk with a mean of 60% of the unconstraining limit and lower and upper bounds of 20% and 100%, respectively. The scenarios (scenario group REG – see Table 3.7) differ with respect to the time at which the final cap is introduced – after year 10 ($t_1$), after year 20 ($t_2$), or only after year 50 ($t_3$), the end of the simulation horizon.

A comparison of the deterministic scenarios of section 1 with the scenarios under regulatory uncertainty of section 2 show how the capacity expansion strategies differ (i) with respect to the selected technology mix (final and stage 1, capacity and production), and (ii) with respect to cost structures. The cost of regulatory uncertainty is quantified as the expected difference in costs between scenario groups DET and REG.
The third section analyzes the impact of market uncertainty under deterministic regulatory conditions. All scenarios covered in this section (scenario group MKT – see Table 3.8) assume a variable gas price, as well as variable capital costs and technological learning of 20% for the emerging technologies solar, wind, and coal CCS.

A comparison of the results of groups DET and MKT shows how hedging against market risk changes the capacity expansion strategy and cost structures.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R10</td>
<td>fixed after year 10, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>R20</td>
<td>fixed after year 20, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>R50</td>
<td>fixed after year 50, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
</tbody>
</table>

Table 3.7: Scenarios with regulatory uncertainty (REG)

The fourth section combines regulatory and market uncertainty in one scenario (R20M – see table 3.9). It is demonstrated that the resulting expansion strategy leads to a higher proportion of emerging technologies than under any of the scenarios introduced in the preceding sections. This has consequences for the installed nominal capacity and the cost structure.

The results under scenario R20M are then compared with those under the scenarios of group MKT to quantify the cost of regulatory uncertainty. In addition, the cost of ignoring uncertainty (COIU) is quantified by replacing the solver’s first-stage expansion decision under R20M with the corresponding first-stage decision under the deterministic scenario D60.

The fifth section analyzes the impact of excluding nuclear, coal, and/or coal CCS (scenario group T – see Table 3.10) from the range of deployment...
Table 3.9: Scenario with regulatory and market uncertainty (R20M)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>fixed after year 20, μ = 60%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
</tbody>
</table>

Technologies are excluded both in isolation and combined. All scenarios assume market uncertainty. All exclusion combinations are first analyzed under regulatory uncertainty and in a second step under the assumption that regulatory uncertainty is removed. The comparison provides guidance to what extent regulators can mitigate the negative cost effect from technology exclusion by introducing regulatory certainty.

Table 3.10: Scenarios with technology exclusion (T)

The sixth section finally compares the chosen 3-stage approach with successive disclosure of information based on stochastic processes with a simpler 2-stage approach (scenario S2R20M – see Table 3.11).

The comparison focuses on differences in outcome of the two approaches with...
respect to chosen technology mixes, reaction to intermediate information, and
timing of expansion decisions.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of decisions</th>
<th>Carbon cap</th>
<th>Gas price and capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2R20M</td>
<td>2</td>
<td>fixed year 20, $\mu = 60%$</td>
<td>all variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 3.11: Scenarios with technology exclusion (S2R20M)

3.5 Formal problem definition

This section provides a formal definition of the problem. For reference, all variables used in this section are listed alphabetically in appendix B.

3.5.1 Global parameters

The multi-period simulation horizon consists of $n^P$ periods of length $n^Y_k$ and decision times $t_k$. A period is represented as a vector of integers spanning the years covered by the period.9

$$
n^P : \text{number of periods} \\
n^T : \text{number of technologies} \\
n^Y : \text{number of years (all periods)} \\
\tilde{t} = (t_0, \cdots, t_n^P) : \text{decision times and end of last period}
$$

A constant interest rate $r$ is used to discount future cash flows.

$$
r : \text{discount rate}
$$

9The three-period setup underlying most scenarios analyzed is defined as follows: $n^P = 3$, $n^T = 7$, $n^Y = 50$, $\tilde{t} = (0, 10, 20, 50)$. 79
\[ df(\Delta t) = \frac{1}{(1+r)^{\Delta t}} : \text{discount factor (\Delta t expressed in years)} \]

### 3.5.2 Basic Problem

The basic stochastic capacity expansion problem is defined as a system \( x_{k+1} = f_k(x_k, u_k, \omega_k) \) with states \( x_k \), controls \( u_k \), and noise \( \omega_k \), and a cost function \( g_k(\cdot) \).

- \( f_k(x_k, u_k, \omega_k) \): transition function
  - \( x_k \): state vector
  - \( u_k \): control vector
  - \( \omega_k \): noise vector
  - \( g_k(\cdot) \): cost function

### 3.5.3 States

The state vectors \( x_k \) at times \( t_k \) comprise the current pre-decision capacity \( \tilde{c}_k \) and build history \( B_k \), the respective historical capital costs \( HC_k \), the current emissions stock \( es_k \), the current (preliminary) emissions cap \( ec_k \), the current capital cost \( cck \), and the current gas price \( gp_k \).

\[
\bar{x} = (\bar{x}_0, \ldots, \bar{x}_{n^P})
\]

\[
\bar{x}_k = \begin{cases} 
(\tilde{c}_0, ec_0, ec_0, gp_0) & k = 0 \\
(\tilde{c}_k, B_k, HC_k, es_k, ec_k, \tilde{c}_k, gp_k) & k = 1, \ldots, n^P 
\end{cases}
\]

The current capacity \( \tilde{c}_k \) at time \( t_k \) comprises the remainder of the legacy capacity \( \tilde{c}_0 \) (after cumulative decay \( \sum dec_k \)) and the cumulative build up to this point.
\[ \vec{c}_k = (c_{k,1}, \ldots, c_{k,n_T}) \]

\[
\begin{align*}
  c_{k,tec} &= \begin{cases} 
    l_{tec} & k = 0 \\
    (1 - \sum_{k'=1}^{k} dec_{k'}) \cdot l_{tec} + \sum_{k'=0}^{k-1} b_{k',tec} & k = 1, \ldots, n^P 
  \end{cases} \\
  \tilde{l}_c &= (l_{c_1}, \ldots, l_{c_{n_T}}) \\
  \tilde{d}_{tec} &= (dec_{1}, \ldots, dec_{n^P}) \\
  B_k &= \begin{pmatrix} 
    \tilde{b}_0 \\
    \vdots \\
    \tilde{b}_{k-1} 
  \end{pmatrix} = \begin{pmatrix} 
    b_{0,1} & \cdots & b_{0,n_T} \\
    \vdots & \ddots & \vdots \\
    b_{k-1,1} & \cdots & b_{k-1,n_T} 
  \end{pmatrix}
\]

The historical cost \( HC_k \) comprises the decision-dependent history of capital costs for all technologies (see section 3.5.5 for more detail).

\[
HC_k = \begin{pmatrix} 
  \tilde{h}_{c_0} \\
  \vdots \\
  \tilde{h}_{c_{k-1}} \\
  \tilde{h}_{c_k} 
\end{pmatrix} = \begin{pmatrix} 
  h_{c_{0,1}} & \cdots & h_{c_{0,n_T}} \\
  \vdots & \ddots & \vdots \\
  h_{c_{k-1,1}} & \cdots & h_{c_{k-1,n_T}} 
\end{pmatrix} \quad k = 0, \ldots, n^P
\]

See sections 3.5.5 and 3.5.6 for further detail on the remaining components of the state vector.

### 3.5.4 Controls

The control \( \bar{u}_k \) comprises the build decision \( \tilde{b}_k \) and the dispatch strategy \( d_{sk} \) at decision time \( t_k \), based on state vector \( \vec{x}_k \).

\[
\bar{u}_k(\vec{x}_k) = (\tilde{b}_k(\vec{x}_k), d_{sk}(\vec{x}_k)) \quad k = 0, \ldots, n^P - 1
\]
The build decision $\vec{b}_k$ denotes the number of plants per technology to be built during period $k + 1$. It is assumed that new capacity during a period comes online in yearly increments to match yearly demand growth.

$$\vec{b}_k(\vec{x}_k) = (b_{k,1}(\vec{x}_k), \ldots, b_{k,n_T}(\vec{x}_k)) \quad k = 0, \ldots, n^P - 1$$

The available capacity $\vec{c}_t$ during any given year of the period $k$ is a function of the capacity $\vec{c}_{t-1}$ and the build decision $\vec{b}_{k-1}$ at the beginning of the period, as well as the decay of the legacy portfolio $dec_k$ and the demand growth during the period (see 3.5.10). At point $t_{k-1}$, the control $\vec{b}_{k-1}$ is the only variable that can be influenced (all other inputs are deterministic or a function of earlier build decisions). $\vec{c}_t$ is therefore written below as a function of $\vec{b}_{k-1}$.

The build decision $\vec{b}_{k-1}$ is constrained by two conditions:

(i) Yearly capacity needs to be sufficient to satisfy demand times a ratio of capacity to demand $rcd^{10}$ during all years and all load blocks of period $k$.

$$\min_{t_{k-1} < t \leq t_k} \min_{1 \leq l \leq n^P} \left( \vec{c}_t(\vec{b}_{k-1}) \cdot \begin{pmatrix} o_{1,t,l}^P \\ \vdots \\ o_{n_T,t,l}^P \end{pmatrix} - rcd \cdot d_{t,l}^P \right) = 0$$

(ii) Residual excess capacity$^{11}$ shall not reach or exceed the output of a single plant of any technology across all years and load blocks of period $k$.

$$\min_{t_{k-1} < t \leq t_k} \min_{1 \leq l \leq n^P} \left( \vec{c}_t(\vec{b}_{k-1}) \cdot \begin{pmatrix} o_{1,t,l}^P \\ \vdots \\ o_{n_T,t,l}^P \end{pmatrix} - rcd \cdot d_{t,l}^P \right) \cdot \frac{1}{\vec{o}_{tec,t,l}} < 1 \quad \forall tec = 1, \ldots, n^T$$

---

$^{10}$For all scenarios here, $rcd = 1.01$.

$^{11}$A small amount of excess capacity is unavoidable, given that investment decisions per technology are constrained to integer multiplies of the respective technology’s standard plant size.
The dispatch strategy $d_{sk}$ is a real number between 0 and 1 and denotes how the goals of cost optimization and emissions optimization are to be weighted during the economic dispatch in period $k + 1$. A value of 0 denotes a pure cost optimization, a value of 1 a pure emissions optimization, and a value between 0 and 1 a weighting of both goals.

$$d_{sk}(\bar{x}_k) \in [0, 1] \quad k = 0, \cdots, n^P - 1$$

### 3.5.5 Noise

The noise vector $\tilde{\omega}_k$ denotes the random disturbance that becomes known immediately after the control $u_k$ at time $t_k$ is fixed. It comprises the (temporary) emissions cap $e_{c_{k+1}}$, the capital costs for all technologies $\tilde{c}_{c_{k+1}}$ at $t_{k+1}$, and the gas price development $\tilde{g}_{p_{k+1}}$ during period $k + 1$.

$$\Omega = \begin{pmatrix}
\tilde{\omega}_0 \\
\vdots \\
\tilde{\omega}_{n^P-1}
\end{pmatrix}$$

$$\tilde{\omega}_k = (e_{c_{k+1}}, \tilde{c}_{c_{k+1}}, \tilde{g}_{p_{k+1}}) \quad k = 0, \cdots, n^P - 1$$

The (temporary) emissions cap $\tilde{c}$ is a bounded normally distributed random walk with yearly steps and scenario-specific initial value $e_{c_0}$, lower bound $l_0$, upper bound $h_0$, stop time $t_{\text{stop}}$, and distribution parameters $\mu_{c_0}$ and $\sigma_{c_0}$. The stop time $t_{\text{stop}}$ determines the year after which the temporary emissions cap (guidance) becomes a fixed policy. For deterministic emissions caps, the stop time is set to zero.

$$\tilde{c}(\omega) = (e_{c_0}(\omega), \cdots, e_{c_{n^P}}(\omega))$$

$$e_{c_0}(\omega) = \max(l_{c_0}, \min(h_{c_0}))$$
\[
\begin{align*}
ec_{t-1}(\omega) + N_{\mu^ec, \sigma^ec}(\omega)) & \quad t = 1, \cdots, n^Y \\
\mu^ec_t &= \begin{cases} 
\mu^ec_0 & t \leq t^{ec}_{stop} \\
0 & t^{ec}_{stop} < t \leq n^Y 
\end{cases} \\
\sigma^ec_t &= \begin{cases} 
\sigma^ec_0 & t \leq t^{ec}_{stop} \\
0 & t^{ec}_{stop} < t \leq n^Y 
\end{cases}
\end{align*}
\]

*Capital costs* are represented as a matrix \(CC\) comprising \(n^T\) independent, technology-specific and decision-dependent random walks with yearly steps and scenario and technology-specific parameters. The random walks are log-normally distributed with shocks from technological learning \(tlk, j(\bar{x})\) occurring one year after each build decision. The shocks are dependent on the capacity expansion in the particular technology: with each doubling of the installed base \(ibk, j\), capital costs are reduced by an amount equal to the technology-specific learning factor \(tlf^i\).

\[
CC(\omega) = \begin{pmatrix} 
\tilde{c}_0(\omega) \\
\vdots \\
\tilde{c}_{n^Y}(\omega)
\end{pmatrix} = \begin{pmatrix} 
cc_{0,1}(\omega) & \cdots & cc_{0,n^T}(\omega) \\
\vdots & \ddots & \vdots \\
cc_{n^Y,1}(\omega) & \cdots & cc_{n^Y,n^T}(\omega)
\end{pmatrix}
\]

\[
cc_{t, tec}(\omega) = \max(lo_{tec}^ec, \min(hi_{tec}^ec, cc_{t-1, tec}(\omega) \cdot (1 - tl_{tec}(\bar{x})) \cdot N_{\mu^tec, \sigma^tec}(\omega)))
\]

\[
tl_{tec}(\bar{x}) = \begin{cases} 
tlf_{tec} \cdot \log_2\left(\frac{ib_{k, tec} + lb_{k, tec}}{ib_{k-1, tec}}\right) & t = t_{i} + 1 \\
0 & otherwise 
\end{cases} \\
ibk_{tec} = \begin{cases} 
l_{tec} & k = 0 \\
ib_{k-1, tec} + lb_{k-1, tec} & k = 1, \cdots, n^P
\end{cases}
\]

\[\footnote{Note that the installed base—different from the existing capacity \(C\) also includes all retired legacy assets, since technological learning is based on total installations.}
\[\footnote{In all market-uncertainty scenarios, \(tlf^i\) is set to 20% for the emerging technologies wind, solar, and coal CCS, and to 0% for all other technologies.}

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The initial, annualized capital cost $cc_{0,k}$ for technology $k$ is derived from the overnight capital cost $cc_{k}^{overnight}$ and the expected useful lifetime $\text{lifetime}_{k}$ of technology $k$.

$$cc_{0,\text{tec}} = \frac{1}{\sum_{t'=1}^{\text{lifetime}_{\text{tec}}}} cc_{k}^{overnight}, \quad \text{tec} = 1, \cdots, n^{T}$$

The gas price is represented as a bounded log-normally distributed random walk $\bar{gp}$ with yearly steps and scenario-specific initial value $gp_{0}$, lower bound $lo^{gp}$, upper bound $hi^{gp}$, and distribution parameters $\mu^{gp}$ and $\sigma^{gp}$.

$$\bar{gp}(\omega) = (gp_{0}^{Y}(\omega), \cdots, gp_{n^{Y}}^{Y}(\omega)) = (\bar{gp}_{0}(\omega), \cdots, \bar{gp}_{n^{P}-1}(\omega))$$

$$\bar{gp}_{k}(\omega) = (gp_{t_{k-1}+1}^{Y}(\omega), \cdots, gp_{t_{k}}^{Y}(\omega)) \quad k = 1, \cdots, n^{P}$$

$$gp_{t}(\omega) = \max(lo^{gp}, \min(hi^{gp}, \bar{gp}_{t-1}(\omega) \cdot N_{\mu^{gp}, \sigma^{gp}}(\omega))) \quad t = 1, \cdots, n^{Y}$$

Note that—while all stochastic processes are formulated as random walks with yearly steps—the noise vector $\omega_{k}$ includes the values of the emissions cap and capital costs for decision times $t_{k+1}$ only, since inter-period values are not relevant for either the cost function or the next state vector. In contrast, the gas price is included in the noise vector as a vector of yearly values. This is required since variable O&M costs are calculated yearly and are a result of the economic dispatch, which is again influenced by the yearly changing gas prices (see section 3.5.7).

### 3.5.6 Transition function

The generic transition function $f(\cdot)$ is defined as follows.

$$\bar{x}_{k} = f_{k}(\bar{x}_{k-1}, \bar{u}_{k-1}, \bar{\omega}_{k-1}) \quad k = 1, \cdots, n^{P}$$
Recall from section 3.5.3 the definition of the state vectors $\bar{x}_k$.

$$\bar{x}_k = \begin{cases} (\bar{c}_0, ec_0, \bar{c}_0, gp_0) & k = 0 \\ (\bar{c}_k, B_k, HC_k, es_k, ec_k, \bar{c}_k, gp_k) & k = 1, \ldots, n_P \end{cases}$$

The transition functions for the individual state vector components are then defined as follows. The term $em^P_k$ denotes the emissions during period $k$ as a result from the economic dispatch (see section 3.5.11 for detail).

$$\bar{c}_k = \bar{c}_{k-1} - dec_k \cdot \bar{c} + \bar{b}_{k-1} \quad k = 1, \ldots, n_P$$

$$B_k = \begin{cases} \begin{pmatrix} b_0 \\ B_{k-1} \end{pmatrix} & k = 1 \\ \begin{pmatrix} \bar{b}_{k-1} \\ B_{k-1} \end{pmatrix} & k = 2, \ldots, n_P \end{cases}$$

$$HC_k = \begin{cases} \begin{pmatrix} \bar{c}_0 \\ HC_{k-1} \end{pmatrix} & k = 1 \\ \begin{pmatrix} \bar{c}_{k-1} \\ HC_{k-1} \end{pmatrix} & k = 2, \ldots, n_P \end{cases}$$

$$es_k = es_{k-1} + em^P_k (\bar{x}_{k-1}, \bar{u}_{k-1}, \bar{\omega}_{k-1}) \quad k = 1, \ldots, n_P$$

$$ec_k = ec_k(\omega) \quad k = 1, \ldots, n_P$$

$$\bar{c}c_k = \bar{c}c_k(\omega) \quad k = 1, \ldots, n_P$$

$$gp_k = gp_k(\omega) \quad k = 1, \ldots, n_P$$

### 3.5.7 Cost function

The total cost $g(\bar{u}, \bar{\omega})$ is defined as the sum of the discounted period costs $g_k$. 

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\[
g(\tilde{u}, \tilde{w}) = \sum_{k=1}^{nP} df(t_{k-1}) g_k(x_{k-1}, u_{k-1}, \omega_{k-1})
\]

The period cost \( g_k(\cdot) \) comprises capital costs \( g_k^{CC}(\cdot) \), fixed O&M costs \( g_k^F(\cdot) \), variable O&M costs \( g_k^V(\cdot) \), and a potential emissions penalty \( g_k^{EP}(\cdot) \)^{14}.

\[
g_k(\cdot) = g_k^{CC}(\cdot) + g_k^F(\cdot) + g_k^V(\cdot) + g_k^{EP}(\cdot) \quad k = 1, \ldots, nP
\]

The capital costs \( g_k^{CC}(\cdot) \) are defined as the sum of the discounted annual capital costs across all years of period \( k \). The annual capital costs build up throughout a given period following the period’s intra-period capacity expansion pattern (see 3.5.10) and are a function of the historical builds \( b_{k, tec} \) and the respective historical annualized capital costs \( h_{c_k, tec} \)^{15}.

\[
g_k^{CC}(\cdot) = \sum_{t=1}^{t_k-t_{k-1}} df(t) \left( \sum_{t'=0}^{k-2} \tilde{b}_{k'} \tilde{h}_{c_k'} + b_{uk}(t) \tilde{b}_{k-1} \tilde{h}_{c_{k-1}}' \right)
\]

Similarly, the fixed O&M costs \( g_k^F(\cdot) \) are defined as the sum of the product of the historical builds up to period \( k \) and the fixed technology-specific annual fixed O&M costs \( \tilde{f}_c \).

\[
g_k^F(\cdot) = \sum_{t=1}^{t_k-t_{k-1}} df(t) \left( \tilde{c}_{k-1} + b_{uk}(t)(de_{c_k} \tilde{c} + \tilde{b}_{k-1}) \right) \quad k = 1, \ldots, nP
\]

\[
\tilde{f}_c = (f_{c_1}, \ldots, f_{c_{nP}})
\]

^{14} In this section, the term (\cdot) is used as a shortcut for the tuple \((x_{k-1}, u_{k-1}, \omega_{k-1})\).

^{15} Note that it is assumed that no capital payments for the legacy portfolio are outstanding.
The variable O&M costs $g_k^V(\cdot)$ are defined as the sum of the discounted annual variable O&M costs $v_{ct}$ during period $k$. The annual variable costs are a result of the economic dispatch, which is formulated as a linear program (see section 3.5.11).

$$g_k^V(\cdot) = \sum_{t=1}^{t_k-t_{k-1}} df(t) \cdot v_{ct}$$

A penalty $g_k^{EP}(\cdot)$ can only occur at the end of the last period $n^P$, under the condition that the total stock of emissions at that time exceeds the final carbon cap.

$$g_k^{EP}(\cdot) = \begin{cases} 0 & k < n^P \\ \left( df(t_{n^P} - t_{n^P-1}) \max(0, es_{n^P-1} + em_k^P(\cdot) - ec_{n^P}) ppt \right) & k = n^P \end{cases}$$

$$em_k^P(\cdot) = \sum_{t_{k-1} < t \leq t_k} em^Y(\cdot)$$

where $ppt$ denotes the emissions penalty per ton.

3.5.8 Demand

Demand $D$ is based on a full year of hourly demand data $\vec{d}_0$ for the year 2012 for the ERCOT region, which is then scaled following an annual growth pattern $\text{growth}$.

$$\vec{d}_0 = (d_{0,1}, \ldots, d_{0,8760})$$

$$\text{growth} = (\text{growth}_1, \ldots, \text{growth}_{n^P})$$

$$D = \begin{pmatrix} \vec{d}_1 \\ \vdots \\ \vec{d}_{n^P} \end{pmatrix} = \begin{pmatrix} d_{1,1} & \cdots & d_{1,8760} \\ \vdots & \ddots & \vdots \\ d_{n^P,1} & \cdots & d_{n^P,8760} \end{pmatrix}$$

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\[ d_{t,h} = \begin{cases} \text{growth}_{t}^{h \text{years}}, d_{0,h} & t = 1 \\ \prod_{t'=1}^{t-1} \text{growth}_{t'} \cdot \text{growth}_{t}^{h \text{years}}, d_{0,h} & 2 \leq t \leq n^{\text{years}} \end{cases} \quad h = 1, \cdots, 8760 \]

### 3.5.9 Partitioning

Demand is partitioned for each year into \( n^{P} \) demand blocks. The peak demand block for a given year \( t \), \( P_{k,1} \), comprises the \( n^{\text{peak}} \) hours with the highest demand of the respective year\(^{16} \). The remaining hours of demand are cut into blocks that are identical with respect to the width of the demand range \( \text{range}^{P}_{k} \) covered.

- \( n^{P} \): size of partition (= number of blocks)
- \( n^{\text{peak}} \): number of hours in peak load block

\[
\mathcal{P} = \begin{pmatrix} P_1 \cdots P_{n^{P}} \\ \vdots \\ P_{n^{P}} \end{pmatrix} = \begin{pmatrix} P_{1,1} \cdots P_{1,n^{P}} \\ \vdots \\ P_{n^{P},1} \cdots P_{n^{P},n^{P}} \end{pmatrix}
\]

\( (P_{t,1}, P_{t,1}) = (\{h_{t,1,1, \cdots, h_{t,1,n^{\text{peak}}}}\},\{1, \cdots, 8760\} \setminus \{h_{t,1,1, \cdots, h_{t,1,n^{\text{peak}}}}\}) \)

\[ \text{s.t. } \min_{h \in P_{t,1}} d_{t,h} \geq \max_{h \in P_{t,1}} d_{t,h} \quad t = 1, \cdots, n^{Y} \]

\[ \text{range}^{P}_{t} = \frac{\max_{h \in P_{t,1}} d_{t,h} - \min_{h \in P_{t,1}} d_{t,h}}{n^{P} - 1} \quad t = 1, \cdots, n^{Y} \]

\[ P_{t,l} = \{h | \min_{h' \in P_{t,1}} d_{t,h'} + (l-2)\text{range}^{P}_{t} \leq d_{t,h} \quad t = 1, \cdots, n^{Y} \}
\]

\[ < \min_{h' \in P_{t,1}} d_{t,h'} + (l-1)\text{range}^{P}_{t} \quad l = 2, \cdots, n^{P} \]

The average demand per year and load block \( D^{P} \) is then calculated as follows.

\(^{16}\)Typically, \( n^{\text{peak}} \) is small (here: 10 for all analyzed scenarios) to realistically account for peak demand.
Peak demand per year and period can then be defined as follows (note that the period 0 value is required as seed value).

\[
D_P = \begin{pmatrix}
  d_{0,1}^P \\
  \vdots \\
  d_{n^Y,1}^P
\end{pmatrix}
= \begin{pmatrix}
  d_{0,1}^P & \ldots & d_{0,n^P}^P \\
  \vdots & \ddots & \vdots \\
  d_{n^Y,1}^P & \ldots & d_{n^Y,n^P}^P
\end{pmatrix}
\]

\[
d_{t,l}^P = \frac{1}{|\mathcal{P}_{t,l}|} \sum_{h \in \mathcal{P}_{t,l}} d_{t,h} \\
\text{for } t = 1, \ldots, n^Y; l = 1, \ldots, n^P
\]

Output \(\bar{o}_k\) per plant of the intermittent technologies wind and solar varies across load blocks. In order to capture the historical correlation between demand \(\bar{d}_0\) and output \(O\), the output datasets are averaged across the same partitioning \(\mathcal{P}\). Available generation for plants of all non-intermittent technologies is assumed to be constant and equal to nominal capacity. Hourly output data for the year 2012 for the ERCOT region was used as basis. This historic output pattern is assumed to remain constant across all years.

\[
O = \begin{pmatrix}
  \bar{o}_1 \\
  \vdots \\
  \bar{o}_{n^T}
\end{pmatrix}
= \begin{pmatrix}
  o_{1,1} & \ldots & o_{1,8760} \\
  \vdots & \ddots & \vdots \\
  o_{n^T,1} & \ldots & o_{n^T,8760}
\end{pmatrix}
\]

\[
O_{\text{tec}}^P = \begin{pmatrix}
  \bar{o}_{\text{tec},1}^P \\
  \vdots \\
  \bar{o}_{\text{tec},n^Y}
\end{pmatrix}
= \begin{pmatrix}
  o_{\text{tec},1,1}^P & \ldots & o_{\text{tec},1,n^P} \\
  \vdots & \ddots & \vdots \\
  o_{\text{tec},n^Y,1}^P & \ldots & o_{\text{tec},n^Y,n^P}
\end{pmatrix} \\
\text{for } \text{tec} = 1, \ldots, n^T
\]

\[
o_{\text{tec},t,l}^P = \frac{1}{|\mathcal{P}_{t,l}|} \sum_{h \in \mathcal{P}_{t,l}} o_{\text{tec},h} \\
\text{for } \text{tec} = 1, \ldots, n^T
\]
3.5.10 Intra-period capacity expansion

An investment decision needs to be large enough so that demand can be satisfied throughout the period following the decision. Since a period typically spans 10, 20, or 30 years and demand is assumed to grow during that period, it would not be realistic to assume that all new capacity comes online in the first year of the period.

Rather, it is assumed that new capacity is added each year of the period to follow the demand growth pattern during the period\(^{17}\). Likewise, it is assumed that retirements of legacy assets during the period follow the same pattern.

Let \( p(t) \) denote the period that includes year \( t \). The buildup pattern \( bu_k \) is then defined as follows (see also 3.5.9).

\[
buk(t) = \frac{\max_{t'_p(t)-1 < t' \leq t} d^{Y}_{p(t)' - d^{P}_{p(t)}}}{d^{P}_{p(t)} - d^{P}_{p(t)-1}} \quad t = 1, \ldots, n^Y
\]

The capacity available during any given year can then be calculated based on the buildup pattern \( bu_k \).

\[
c_t^Y = (c_{t,1}^Y, \ldots, c_{t,n^Y}^Y) \\
c_{t,tec} = c_{p(t)-1} + bu_{p(t)}(t) \left( dec_{p(t)} i_{tec} + b_{p(t)-1,tec} \right) \quad tec = 1, \ldots, n^T
\]

\(^{17}\)Example: Assume an investment decision at the beginning of a period comprises 10 plants of a certain technology, and demand growth during the period amounts to 10 GW. Assume furthermore that demand has increased by 4 GW from the beginning of the period to the end of year 3. Then 4 of the new plants are assumed to be online throughout the year.
3.5.11 Economic dispatch

The economic dispatch process returns the dispatch decision \( \tilde{d}_{pt}(\cdot) \) as well as the resulting variable cost \( vct(\cdot) \) and carbon emissions \( em_t^Y(\cdot) \) during year \( t \), based on the state \( \tilde{x}_{pt}(t-1) \), control \( \tilde{u}_{pt}(t-1) \), and noise \( \tilde{\omega}_{pt}(t-1) \), where \( p(t) \) denotes the period in which year \( t \) falls. To calculate the optimal dispatch, the dispatch function receives a subset of the data included in \( (x_{pt}(t-1), u_{pt}(t-1), \omega_{pt}(t-1)) \), in particular: the existing generating capacity in year \( t \), the dispatch strategy \( d_{sp}(t) \), and the gas price \( gp_t \) in year \( t \). The term \( dp_{t,tec,i} \) denotes the number of dispatched plants for each technology \( tec \) and each load block \( l \) of year \( t \).

\[
\tilde{d}_{pt}(\cdot) \text{: dispatch decision for year } t \\
vct : \text{total variable cost during year } t \\
vct^H : \text{hourly variable cost per plant of technology } k \\
em_t^Y : \text{total carbon emissions during year } t \\
em_k^H : \text{hourly carbon emissions per plant of technology } k \\
p(t) : \text{period that includes year } t
\]

\[
\tilde{d}_{pt}(\cdot) = \tilde{d}_{pt}(\tilde{x}_{pt}(t-1), \tilde{u}_{pt}(t-1), d_{sp}(t-1), gp_t)
\]

\[
\begin{pmatrix}
dp_{t,1,1}(\cdot) \\
\vdots \\
dp_{t,1,n^p}(\cdot) \\
\vdots \\
dp_{t,n^p,1}(\cdot) \\
\vdots \\
dp_{t,n^p,n^p}(\cdot)
\end{pmatrix}
\]

\[
t = 1, \ldots, n^Y
\]

\[
vct(\tilde{d}_{pt}, gp_t) = \sum_{tec=1}^{n^p} \sum_{l=1}^{n^p} dp_{t,tec,l} vct^H(gp_t) |P_{t,l}| \
\]

\[
t = 1, \ldots, n^Y
\]

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The hourly variable cost per plant comprise fuel-related variable cost and other variable cost. The fuel-related variable cost are defined as the product of heat rate, capacity per plant, and fuel price.

\[
vc_{tec}(gp) = vc_{tec}^{H, fuel}(gp) + vc_{tec}^{H, other}
\]

\[
= \text{heatrate}_{tec} \cdot gp \cdot \text{capacity}_{tec} + \text{vc}_{tec}^{H, other} \quad \text{tec} = 1, \ldots, n^T
\]

The dispatch optimization is based on two linear programs.

\( lp_t^{cost} \): solving for lowest cost in year \( t \) under emissions constraint
\( lp_t^{em} \): solving for lowest emissions in year \( t \) under cost constraint

The dispatch decision \( \ddp_t(\cdot) \) is the result of three linear optimization: In a first pass, the cost-optimized solution without emissions constraints is calculated and the resulting emissions are recorded as \( em_t^{hi} \).

\[
\ddp^{step 1} = lp_t^{cost}(\overbar{d}_t, \overbar{P}_t, \overbar{c}_{p(t)}-1, \overbar{b}_{p(t)}-1, +\infty)
\]

\[
em_t^{hi} = em_t(Y (\ddp^{step 1})) \quad t = 1, \ldots, n^Y
\]

where \( d_t \) denotes the average demand per load block in year \( t \), \( \overbar{P}_t \) the load blocks (each load block expressed as a set of hours) in year \( t \), and \( \overbar{c}_{p(t)}-1 \) and \( \overbar{b}_{p(t)}-1 \) the available capacity and the control at the beginning of period \( p(t) \). The fifth parameter represents the emissions constraint (in this case \(+\infty / unconstrained\)).
In a second pass, the emissions-optimized solution is calculated and the resulting emissions are recorded as $e_{m_t}^{lo}$.

$$\hat{d}^*_{p_t} = l_{p_t}^{em}(d_t^P, \bar{P}_t, \bar{c}_p(t)-1, \bar{b}_p(t)-1, +\infty)$$

$$e_{m_t}^{lo} = e_{m_t}^{Y}(\hat{d}^*_{p_t}, t)$$

$t = 1, \ldots, n^Y$

In a third and final pass, a weighted emissions constraint $e_{m_t}^{max}$ is defined based on the dispatch strategy $d_{s_{p(t)-1}}$, and the cost-optimized solution under this emissions constraint is then returned as the final dispatch solution for year $t$.

$$e_{m_t}^{max} = d_{s_{p(t)-1}} \cdot e_{m_t}^{lo} + (1 - d_{s_{p(t)-1}}) \cdot e_{m_t}^{hi}$$

$$\hat{d}^*_{p_t} = l_{p_t}^{cost}(d_t^P, \bar{P}_t, \bar{c}_p(t)-1, \bar{b}_p(t)-1, e_{m_t}^{max})$$

$t = 1, \ldots, n^Y$

The linear program $l_{p_t}^{cost}$ is defined as follows.\textsuperscript{18}

$$l_{p_t}^{cost}(\cdot) = \arg\min_{r \in \mathbb{R}^{n_P}} (f_t^{cost} \cdot r) \mid \mathcal{X}_t^{cost} \cdot r \geq b_t^{cost} \land r \leq u_t^{cost} \cdot n^T$$

The structure of the LP formulation is as follows: the solution vector $r$ contains the number of plants of each technology deployed during each load block, sorted first by technology and then by load block. Accordingly, the length of the solution vector is $n^T n^P$ (or $(n^T - 2) \cdot n^P$ for the net demand approach with two renewable technologies). The objective function $f_t^{cost}$ is defined as a vector denoting the hourly variable O&M cost for each technology times the number of hours for each load block. The matrix $\mathcal{X}_t^{cost}$

\textsuperscript{18}Note that, in the interest of clarity, the formulation shown here is a simplification of the actual implementation, which is based on net demand. The net-demand approach assumes that wind and solar dispatch fully at all times, and that the dispatch optimization is therefore only considering the non-renewable generators to satisfy demand that is lowered by the demand block-specific output from wind and solar.
comprises an upper matrix $\hat{y}_t^{\text{cost}}$ denoting the output per plant, and a lower matrix $\mathbf{A}_t^{\text{cost}}$ denoting the emissions per plant of each technology during each load block. The lower bound constraint $\mathbf{b}_t^{\text{cost}}$ ensures that the minimum output satisfies demand during each load block, and that total emissions stay below the defined limit $em_{\text{max}}$. Finally, the upper bound $\mathbf{u}b_t^{\text{cost}}$ limits the number of plants of each technology dispatched during each load block to the available capacity.

\[
\begin{align*}
\mathbf{h}_t^{\text{cost}} &= \begin{pmatrix}
    vc_1^H \cdot |P_t, 1| \\
    \vdots \\
    vc_l^H \cdot |P_t, n_T|
\end{pmatrix} \\
    t &= 1, \ldots, n_Y \\

\mathbf{A}_t^{\text{cost}} &= \begin{pmatrix}
    \hat{y}_t^{\text{cost}}_{1,1} & \cdots & \hat{y}_t^{\text{cost}}_{1,n_T} \\
    \vdots & \ddots & \vdots \\
    \hat{y}_t^{\text{cost}}_{l,1} & \cdots & \hat{y}_t^{\text{cost}}_{l,n_T}
\end{pmatrix} \\
    t &= 1, \ldots, n_Y \\

\mathbf{\hat{A}}_{t, \text{tec}} &= \begin{pmatrix}
    \hat{o}_{t, \text{tec}, 1}^P & \cdots & 0 \\
    \vdots & \ddots & \vdots \\
    0 & \cdots & \hat{o}_{t, \text{tec}, n_T}^P
\end{pmatrix} \\
    t &= 1, \ldots, n_Y; \text{tec} = 1, \ldots, n_T \\

\mathbf{\hat{A}}_{t, \text{tec}} &= -\begin{pmatrix}
    (em_{\text{tec}}^H \cdot |P_t, 1|, \cdots, em_{\text{tec}}^H \cdot |P_t, n_T|)
\end{pmatrix} \\
    t &= 1, \ldots, n_Y; \text{tec} = 1, \ldots, n_T \\

\mathbf{b}_t^{\text{cost}} &= \begin{pmatrix}
    \bar{d}_t^{P} \\
    -em_{\text{max}}
\end{pmatrix} \\
    t &= 1, \ldots, n_Y \\

\mathbf{u}b_t^{\text{cost}} &= \begin{pmatrix}
    t_t^Y \\
    \vdots \\
    t_t^Y
\end{pmatrix} \\
    t &= 1, \ldots, n_Y
\end{align*}
\]
The formulation of the LP program $l_{p_k}^{em}$ is similar to that of $l_{p_k}^{cost}$: the objective function and $\mathcal{A}$ are swapped, and the upper bound on emissions $\text{em}_{t}^{\text{max}}$ is replaced by an upper bound on cost $\text{cost}_{t}^{\text{max}}$.

$$l_{p_t}^{em}(\cdot) = \arg\min_{x \in (\mathbb{R}^+)^{n_T}} \left( \sum_{i \in P_t} e_{i}^{em} \cdot x_i \mid \mathcal{A}_t^{em} \cdot x \geq b_t^{em} \land x \leq \text{ub}_t^{em} \right) \quad t = 1, \ldots, n^Y$$

$$f_t = \begin{pmatrix} e_{m_1} & \cdots & e_{m_{n^Y}} \\ \vdots & \ddots & \vdots \\ e_{m_{n^Y}} & \cdots & e_{m_{n^Y}} \end{pmatrix} \quad t = 1, \ldots, n^Y$$

$$\mathcal{A}_t = \begin{pmatrix} \hat{A}_{t,1} & \cdots & \hat{A}_{t,n_{TEC}} \\ \hat{A}_{t,1} & \cdots & \hat{A}_{t,n_{TEC}} \end{pmatrix} \quad t = 1, \ldots, n^Y$$

$$\hat{A}_{t,\text{TEC}} = \begin{pmatrix} o_{t,\text{TEC},1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & o_{t,\text{TEC},n_T} \end{pmatrix} \quad t = 1, \ldots, n^Y; \text{tec} = 1, \ldots, n_T$$

$$\hat{A}_{t,\text{TEC}} = -(v_{\text{TEC}} \cdot |P_{t,1}|, \ldots, v_{\text{TEC}} \cdot |P_{t,n_T}|) \quad t = 1, \ldots, n^Y; \text{tec} = 1, \ldots, n_T$$

$$b_t = \begin{pmatrix} (d_t^{\text{TEC}})' \\ -\text{cost}_{t}^{\text{max}} \end{pmatrix} \quad t = 1, \ldots, n^Y$$

$$\text{ub}_t^{em} = \begin{pmatrix} c_{t,1}^{Y} \\ \vdots \\ c_{t,n_{TEC}}^{Y} \\ \vdots \\ c_{t,n_{TEC}}^{Y} \end{pmatrix} \quad t = 1, \ldots, n^Y$$
Chapter 4

Approach

4.1 Problem category and potential approaches

The problem belongs to the class of sequential decision making problems under uncertainty. Decision making is central (as opposed to agent based). State space, decision space and random noise are defined in continuous, mesh-free spaces, and the system is decision-dependent with respect to technological learning (capital costs for emerging technologies reduce with investments in these technologies – see section 3.3.5).

These characteristics guided the choice of the solution approach.

Two approaches are widely used to analyze the general problem class: stochastic programming [6] and approximate dynamic programming (ADP) [32, 33].

While both approaches are suited to handle high-dimensional multi-stage problems in continuous space, stochastic programming methods typically do not allow for incorporating decision dependency.

Accordingly, approximate dynamic programming was chosen to solve for an optimal expansion policy.

Once a capacity decision has been taken at a decision time $t_k$, variable O&M costs are driven by the dispatch decisions during each period of operation. Dispatch optimization is formulated as a linear program. Accordingly, a linear solver is embedded to find an optimal dispatch solution given a particular technology mix and demand pattern.
4.2 Algorithm

The ADP algorithm is implemented in MATLAB using object-oriented structures and calling CPLEX as the linear solver for the economic dispatch.

This section documents and discusses the high level structure of the central parts of the solver in pseudo code. A full documentation is beyond the scope of this document.

4.2.1 Main solver loop

The pseudo-code for the main solver loop (function `solve`) is listed as algorithm 1.

Algorithm 1 solve

```plaintext
function SOLVE

—Step 1: Create bootstrap set
for i = 1:nBootstrap do
  —Find random path—
  [states controls costsForward] = TWOPASS(1,'random');
  —Add new points to surface—
  UPDATESURFACE(states,controls,costs);
end for

—Step 2: Calibrate surface norm—
CALIBRATENORM;

—Step 3: Explore—
for i = 1:nExplorations do
  —Create a new path—
  [states controls costsForward] = TWOPASS(1,'explore');
  —Add new points to surface—
  UPDATESURFACE(states,controls,costsForward);
end for

—Validate surface—
[states controls costsForward] = RECALCSURFACE;
—Add re-validated and new points to surface—
UPDATESURFACE(states,controls,costsForward);
end function
```

In step 1, the solver generates a set of random build decisions and corresponding states (the bootstrap set) via a two-pass approach. Bootstrapping is often used in ADP to create a rough initial (sub-optimal) value surface that is then used during the exploration phase as a starting point.
In step 2, the *normalization vectors* are calibrated: The different dimensions of the state vector can greatly differ with respect to the range of values they can contain. For example, the gas price will usually take values between 0 and 40, whereas the emissions cap can take values between 1.9 and 9.3 billion. Since the solver relies on Euclidean distance measures, range differences of that magnitude would create unintended search results and value estimates. All state and control variables are therefore projected to a normalized n-dimensional space \([0, 1]^n\) via normalization vectors before they are added to the surface of visited points. The vectors are generated after the bootstrapping based on the bootstrap sample\(^1\).

Step 3 describes the exploration phase. The step starts with the search for a new optimal path (or set of states, controls). The new path is then added to the set of already visited points (the *surface*). The step concludes with a recalculation of the surface (see below for an explanation of the recalculation algorithm)\(^2\).

### 4.2.2 Two-pass search

The two-pass search returns a path from a defined starting point to the end of the simulation horizon. A full path consists of the vector of states \(x = (x_0, \ldots, x_n^-)\), the vector of controls \(u = (u_0, \ldots, u_{n^-1})\), and the associated forward costs per state.

A forward path is constructed by consecutively moving (i) from the pre-decision vector \(x_k^-\) at the beginning of period \(k\) to the post-decision vector \((x_k^+, u_k^-)\) of the same period (\(0 \leq k < n^P - 1\)), and (ii) from that post-decision vector to the pre-decision vector \(x_{k+1}^- = f(x_k^+, u_k^-, w_k^-)\) of the next period (where \(x_n^-\) represents the final state vector).

Controls \(u_k^-\) can be either taken randomly (calling function *decideStepRandom*) or as an exploration step (calling function *decideStep*, explained in more detail below). The random noise for a respective period is then added via function *postToPre*. This function in parallel returns the cost to go for the specific period.

\(^1\)The actual solve algorithm calls the calibration function regularly during the exploration phase to ensure that the search space remains normalized.

\(^2\)The actual solve algorithm performs explorations and updates in batches: new points are added typically only after a pre-defined number of explorations, to improve performance.
Once the forward path is complete, the backward path adds the actual discounted forward cost at the beginning of each period $k$.

Note that the starting point can be either be the generic starting state at $t_0$ or an existing surface point. This feature allows for later re-validation of existing points (function $recalcSurface$, see below).

### 4.2.3 Step search

The search for the optimal control, function $decideStep$, given a pre-decision state $statePre$ at time $t_k$, is shown in a simplified form as algorithm 3. $decideStep$ consists of an initialization and two steps: (i) identify the lowest cost control found so far and define this control as a starting point; (ii) search for a better solution in the neighborhood of the starting point.

During initialization, the function $getVectorPre$ reduces the fully expanded state $statePre$ to a normalized, reduced vector $vectorPre$ containing only the information relevant to find the next-step control. This reduces the dimensionality of the problem.

In step 1, of all post-decision states visited so far\(^3\), the $nNearest$, measured by the Euclidean distance of their pre-decision component to $vectorPre$, are pre-selected. Of that pre-selection, the control of the post-decision state with the lowest forward cost is selected as starting point for the step 2.

In step 2, the neighborhood of the starting point is then searched for a lower cost solution. During the search, each dimension of the control (builds per technology and dispatch strategy) is selected and then modified upwards and downwards within a pre-defined range. For each modified control, its forward cost is then estimated by calling the function $estVal$, and the modified control with the lowest forward cost is selected as the starting point for the search along the next dimension. The function returns the estimated optimal control once the neighborhood search is complete (i.e., after considering all dimensions).

Note that, different from the simplified version documented here, the actual implementation of $decideStep$ incorporates a certain amount of randomness with respect to (i) the selection of the entry point in step 1, (ii) the order of the dimensions of the control that are modified in step 2, and (iii) the

\(^3\)Post-decision states are stored as a structure consisting of a pre-decision state, a control, and the average, discounted forward cost.

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Algorithm 2 twoPass

function twoPass(periodIn, pointIn, method)
-- Step 1: Initialize --
if (periodIn = 1) and (pointIn = 0) then
  -- Create generic initial state --
  state{1} = POSTToPRE(0, 0, 0);
  periodInExplore = periodIn;
else if pointIn > 0 then
  -- Retrieve initial state and control --
  state{periodIn} = surface{periodIn}.state{pointIn}
  control{periodIn} = surface{periodIn}.control{pointIn}
  -- Move to next stage --
  [state{periodIn+1}, costStep{periodIn}]
  = POSTToPRE(periodIn, state{periodIn}, control{periodIn});
  periodInExplore = periodIn + 1;
end if

Step 2: Forward pass
for i = periodInExplore:nPeriods do
  -- Find a control --
  if method = 'explore' then
    -- Find optimal control --
    control{i} = DECIDESTEP(i, state{i});
  else if method = 'random' then
    Find random control --
    control{i} = DECIDESTEPRANDOM(i, state{i});
  end if
  -- Move to next stage --
  [state{i+1}, costStep(i)]
  = POSTToPRE(i, state{i}, control{i});
end for

Step 3: Backward pass
costForward(nPeriods) = costStep(nPeriods);
for i = (nPeriods-1):-1:periodIn do
  costForward(i) = costStep(i) + discountFactorPeriod(i) * costForward(i+1);
end for
return [state control costForward]
end function
selection of the optimal modified control in step 2. Random decisions are used to reduce the risk of early convergence. The amount of randomness is parameterized.

**Algorithm 3 decideStep**

```plaintext
function DECIDESTEP(period,statePre)
    - Step 0: Init —
        vectorPre = GETVECTORPRE(period,statePre);
    - Step 1: Select starting point—
        if (period > 1) then
            idxFeasible = GETNEAREST(period,vectorPre,nNearest);
        else
            idxFeasible = 1:size(surface{period});
        end if
        idxBest = argmin(surface{period}.costForward(idxFeasible));
        controlBest = surface{period}.control{idxBest};
        [statePost vectorPost] = GETSTATEPOST(period,statePre,controlBest);
        estCost = ESTVAL(period,vectorPost);
    - Step 2: Search neighborhood for better solution—
        for i = 1:nTech+1 do
            controlsTry = EXPANDBUILD(period,statePre,controlBest,i);
            for j = 1:size(controlsTry) do
                [statePost vectorPost] = GETSTATEPOST(period,statePre,controlsTryi);
                costTry(k) = ESTVAL(period,vectorPost);
            end for
            idxBest = argmin(costTry);
            controlBest = controlsTry(idxBest);
            costBest = costTry(idxBest);
        end for
        return [controlBest costBest]
end function
```

4.2.4 Value estimation

To estimate the value of a post-decision state (see algorithm 4), the closest neighbors of stored post-decision states are retrieved from the respective surface. The number of neighbors selected, \( n_{Neighbors} \), is set to twice the dimension of the search space / the length of the post-decision vector.
In a second step, all points are weighted using an exponential function (see [33])

\[
weight_i = \frac{c_i \cdot e^{-dist_i^2}}{\sum_{j=1}^{n_{Neighbors}} c_j \cdot e^{-dist_j^2}} \quad i = 1, \ldots, n_{Neighbors}
\]

where \( dist_i \) denotes the Euclidean distance between neighbor \( i \) and the search point and \( c_i \) the number of times that neighbor \( i \) has been valued/visited.

Finally, the weighted average of all neighbors is returned as the value estimate for the post-decision state.

**Algorithm 4 estVal**

```plaintext
function ESTVAL(period, vectorPost)
    nNeighbors = length(vectorPost) * 2;
    [nearestIdx nearestDist] = GETNEAREST(period, vectorPost, nNeighbors);
    c = surface{period}.nVisits(nearestIdx);
    y = surface{period}.costForward(nearestIdx);
    for i = 1:nNeighbors
        weight(i) = exp(-nearestDist(i) * nearestDist(i)) * c(i);
    end for
    val = transpose(y) × weight / sum(weight);
    return [val]
end function
```

### 4.2.5 Surface recalculation

The surface recalculation improves the quality of the surface with respect to the values of each saved state on the surface: if valued only once, a post-decision state could attract a forward cost that deviates widely from the expected forward cost of that state, if, e.g., during a sample an unusually low or high carbon cap was observed randomly. If a state gets allocated a forward cost that is far larger than its average value would be, the optimizer gets wrongly discouraged to search in the neighborhood of that point. Conversely,
if a point gets allocated a forward cost that is much smaller than the average value would be, that point could become a false "attractor".

The function `recalcSurface` ensures that all saved points are visited and their forward costs are calculated at least `paraMinVisits` number of times. Via function `updateSurface`\(^4\), the forward costs during all visits are averaged.

Note that the recalculation of a given state at a given stage, by calling function `twoPass`, typically creates new states at succeeding stages. This leads to a situation where at any given time the later-stage surfaces are typically denser (have more states) than the early stage surfaces. Experiments with different values for `paraMinVisits` have shown that the algorithm converges fastest for values of either 2 or 3.

**Algorithm 5 recalcSurface**

```plaintext
function RECALCSURFACE(vectorPost)
    for i = nPeriods:-1:1 do
        idxUpdatePoints = find(surface{i}.nVisits < paraMinVisits);
        nUpdates = length(idxUpdatePoints);
        for j = 1:nUpdates do
            [statesTmp controlsTmp costForwardTmp] = TWOPASS(i,idxUpdatePoints(j),'explore')
            for k = i:nPeriods do
                states{k}{end+1} = statesTmp{k};
                controls{k}{end+1} = controlsTmp{k};
                costForward{k}(end+1) = costForwardTmp(k);
            end for
        end for
    end for
    return [states controls costForward]
end function
```

\(^4\)Function `updateSurface` (not documented here) stores new pre-decision and post-decision states in the respective surfaces. If a state already exists on a surface, it is not stored again as a new point but its forward cost is updated.
Chapter 5

Results

The following results chapter is organized in six main sections.

The first section analyses five fully deterministic scenarios under a range of carbon caps. These deterministic cases serve as a reference for subsequent scenarios with uncertainty. They also build the basis to evaluate the cost of ignoring uncertainty and the cost of regulatory uncertainty.

The second section introduces regulatory uncertainty. Here, the carbon cap is the result of a random walk that is stopped after year 10, year 20, or only after year 50, the end of the simulation horizon. The scenarios under regulatory uncertainty are compared with the deterministic scenarios of the first section, and the concept of the cost of regulatory uncertainty is introduced.

The third section analyzes the impact of market uncertainty under deterministic regulatory conditions. All scenarios covered in this section assume a variable gas price, as well as variable capital costs and technological learning for the emerging technologies solar, wind, and coal CCS.

The fourth section combines regulatory and market uncertainty in one scenario. This leads to materially different results than under pure regulatory uncertainty or market uncertainty. The results are then compared with those under market uncertainty to quantify the cost of regulatory uncertainty. In addition, the cost of ignoring uncertainty (COIU) is quantified by replacing the solver’s first-stage expansion decision under R20M with the corresponding first-stage decision under the deterministic scenario D60.

The fifth section analyzes the impact of excluding nuclear, coal, and/or coal

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CCS from the range of deployment options. Technologies are excluded both in isolation and combined. All scenarios assume market uncertainty. All exclusion combinations are first analyzed under regulatory uncertainty and in a second step under the assumption that regulatory uncertainty is removed. The comparison provides guidance to the extent regulators can mitigate the negative effects from technology exclusion by introducing regulatory certainty.

Finally, the sixth section compares the chosen 3-stage approach with a simpler 2-stage approach. The comparison focuses on differences in outcome of the two approaches with respect to chosen technology mixes, reaction to intermediate information, and timing of expansion decisions. The analysis gives guidance with respect to improvements that could be expected from a further increase in decision steps.
5.1 The deterministic cases

Five deterministic scenarios (see Table 5.1) are introduced. They differ only in the carbon cap: scenario D20 assumes the strictest carbon cap at 20% of the unconstrained quantity. The cap is then relaxed in four consecutive steps of 20 percentage points each. D100 represents the case where the carbon cap is not constraining the solution.

The purpose of the deterministic scenarios is to serve as a baseline for scenarios that include uncertainty. In addition, the results of the deterministic scenarios can be easily replicated with a standard non-linear programming (NLP) formulation. This comparison serves to validate the ADP algorithm.

All results are based on learning over 30,000 sample runs (explores).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>fixed 20%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D40</td>
<td>fixed 40%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D60</td>
<td>fixed 60%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D80</td>
<td>fixed 80%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>D100</td>
<td>fixed 100%</td>
<td>fixed</td>
<td>fixed</td>
</tr>
</tbody>
</table>

Table 5.1: Deterministic scenarios (DET)

5.1.1 Total cost and emissions

Table 5.2 shows the total costs and emissions (mean and standard deviation) generated under each scenario. The scenario with the strictest carbon cap (D20), is 50% more expensive than the unconstrained scenario (D100).

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>D20</td>
<td>221.2</td>
<td>2.3</td>
</tr>
<tr>
<td>D40</td>
<td>182.8</td>
<td>1.6</td>
</tr>
<tr>
<td>D60</td>
<td>164.3</td>
<td>2.0</td>
</tr>
<tr>
<td>D80</td>
<td>154.9</td>
<td>0.4</td>
</tr>
<tr>
<td>D100</td>
<td>147.5</td>
<td>0.3</td>
</tr>
</tbody>
</table>

Table 5.2: Deterministic scenarios - total cost and emissions
The increase in cost is not linear. Relaxing the constraint by 20 percentage points from the strictest to the second-strictest scenario (D20 to D40) yields cost savings of $38 M, compared with only $7 M of cost savings between the second-least constrained and the unconstrained scenario (D80 and D100) (see Figure 5.1).

![Graph showing total NPV - mean](image)

Figure 5.1: Total cost

### 5.1.2 Capacity expansion

Figure 5.2 and Table 5.3 show the total capacity by technology, measured by average available output during peak demand hours\(^1\), at the end of the 50-year planning horizon. The mix consists of almost exclusively nuclear power stations and gas generators (both combined-cycle and single-cycle). The negligible contributions from other technologies can be explained by the approximate nature of the solution algorithm and would disappear after more iterations.

\(^1\) Capacity during peak demand and nominal capacity differ in the case of the variable energy resources wind (12 MW vs. 100 MW per standard installation) and solar (91 MW vs. 150 MW per standard installation).
Nuclear stations are only added to the mix if and to the extent needed to fulfill stricter emissions regulation. For the unconstrained scenario D100, the model solution consists of a gas-only mix.

Figure 5.2: Final capacity

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>61.4%</td>
<td>0.3%</td>
<td>0.5%</td>
<td>0.4%</td>
<td>22.8%</td>
<td>14.6%</td>
<td>0.1%</td>
</tr>
<tr>
<td>D40</td>
<td>46.3%</td>
<td>0.2%</td>
<td>0.3%</td>
<td>0.3%</td>
<td>31.6%</td>
<td>21.3%</td>
<td>0.1%</td>
</tr>
<tr>
<td>D60</td>
<td>37.0%</td>
<td>0.2%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>39.2%</td>
<td>23.4%</td>
<td>0.0%</td>
</tr>
<tr>
<td>D80</td>
<td>16.8%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>56.7%</td>
<td>26.1%</td>
<td>0.0%</td>
</tr>
<tr>
<td>D100</td>
<td>0.0%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>65.1%</td>
<td>34.1%</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

Table 5.3: Final capacity – contribution by technology

Figure 5.3 presents the timing of capacity expansion for scenario D60. The figure shows the capacity mix at the beginning of the simulation and during each of the three periods. Capacity comprises both the remaining legacy portfolio and the new build up to the respective period. The graph shows how both legacy coal and nuclear capacity are fully replaced by gas generators during the first two build decisions at $t_0$ (beginning of the simulation) and
Only during the last capacity expansion decision at $t_2$ (after 20 years), new nuclear capacity is added to the mix. This behavior can be explained by the high capital cost of nuclear plants. At the assumed discount rate of 10% per year, it is rational to delay the construction of nuclear plants as long as possible while still complying with the cumulative carbon cap at the end of the 50-year horizon.

Similar timing with respect to capacity expansion is present in the optimal strategies for all four carbon constrained deterministic scenarios D20 to D80.

![Figure 5.3: Timing of build-up, D60](image)

### 5.1.3 Production

Figure 5.4 and Table 5.4 show the contribution of each technology to total production. Under the most stringent carbon cap, energy originates mainly from nuclear units, gas units, and the available legacy wind generators. However, under less restrictive carbon caps, the inexpensive, but carbon-emitting legacy coal units have a more pronounced role.
Figure 5.4: Total production across all periods

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>76.0%</td>
<td>3.1%</td>
<td>0.2%</td>
<td>0.4%</td>
<td>18.4%</td>
<td>1.1%</td>
<td>0.8%</td>
</tr>
<tr>
<td>D40</td>
<td>54.8%</td>
<td>2.6%</td>
<td>0.2%</td>
<td>0.4%</td>
<td>38.0%</td>
<td>2.0%</td>
<td>2.1%</td>
</tr>
<tr>
<td>D60</td>
<td>38.1%</td>
<td>3.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>49.0%</td>
<td>2.9%</td>
<td>6.6%</td>
</tr>
<tr>
<td>D80</td>
<td>19.1%</td>
<td>2.4%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>69.7%</td>
<td>2.1%</td>
<td>6.5%</td>
</tr>
<tr>
<td>D100</td>
<td>3.8%</td>
<td>2.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>80.0%</td>
<td>5.5%</td>
<td>8.3%</td>
</tr>
</tbody>
</table>

Table 5.4: Total production – contribution by technology
Figure 5.5 shows the dispatch results in period 1. It confirms that the model prioritizes the technologies with the lowest variable costs: in all five scenarios, all of the available legacy nuclear resources are dispatched, while legacy coal generation is added to the extent that still enables compliance with the respective carbon cap.

![Production in period 1](image)

**Figure 5.5: Production in period 1**

### 5.1.4 Using screening curves to explain the results

The results for the deterministic scenarios can be explained by two sets of screening curves.

Figure 5.6 shows the total cost of each technology per kW as a function of operating hours, and absent any emission penalty. Assumptions mirror those used in the simulation, and total costs comprise annualized capital cost, annual fixed O&M cost, and variable O&M cost.

The first set of screening curves show that the lowest cost options are single-cycle gas combustion turbines, if operated for a maximum of 2,214 hours per year, and combined-cycle gas generators, if operated for more than 2,214
hours per year. This is a result of current low natural gas prices in the United States and demonstrates why gas generators have been displacing both nuclear and coal units as base load technology in recent years.

The screening curves also explain the optimal capacity expansion strategy under the unconstrained scenario D100 of a gas-only generation mix.

The screening curves change with the inclusion of an emission penalty though. Figure 5.7 shows the total cost of each technology per kW, assuming that total emissions have reached the cumulative cap and that the marginal kWh would therefore trigger an increase in the emission penalty. In such a scenario, nuclear becomes the least expensive technology, once operated for more than 3,266 hours per year. Below that threshold, the two gas technologies again represent the cheapest option.

The optimal investment strategies under the four constrained scenarios D20 to D80 can all be explained approximately as a weighted mix of the two screening curves. For the most stringent carbon cap (D20), the capacity expansion strategy produces a mix that most closely resembles the capacity mix suggested by Figure 5.7. As the emission constraint is lifted, total
capacity at the end of the simulation horizon approaches the mix shown in Figure 5.6.

![Screening Curve - After Breach of Carbon Cap](image)

Figure 5.7: Screening curve, assuming breach of emissions cap

Note that this is an approximate argument. Screening curves do for example not take into account the intermittent nature of wind and solar. They can therefore not fully explain the strategy produced by the ADP algorithm.

5.1.5 Comparison of results between ADP and NLP frameworks

As an additional quality check, the deterministic cases were solved using a standard non-linear programming (NLP) model (implemented using MATLAB’s FMINCON). The results were then compared to the results produced by the ADP model. Table 5.5 shows a comparison of total costs under all scenarios. The two approaches produce very similar results with differences ranging from -2.3% to +2.6%.

2 The penalty is assumed to be due at the end of the 50-year simulation horizon and is discounted at an annual rate of 10%.
<table>
<thead>
<tr>
<th>Config</th>
<th>Total cost ADP (BN$)</th>
<th>Total cost NLP (BN$)</th>
<th>Delta ADP / NLP</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>221.2</td>
<td>215.6</td>
<td>+2.6%</td>
</tr>
<tr>
<td>D40</td>
<td>182.8</td>
<td>178.7</td>
<td>+2.3%</td>
</tr>
<tr>
<td>D60</td>
<td>164.3</td>
<td>166.4</td>
<td>-1.3%</td>
</tr>
<tr>
<td>D80</td>
<td>154.9</td>
<td>158.5</td>
<td>-2.3%</td>
</tr>
<tr>
<td>D100</td>
<td>147.5</td>
<td>146.3</td>
<td>+0.8%</td>
</tr>
</tbody>
</table>

Table 5.5: Comparison of ADP and NLP results: total costs

Figure 5.8 gives an overview of the final capacity by technology (compare with Figure 5.2). Again, both approaches produce very similar results, although the NLP results include a wind component which replaces some nuclear capacity, particularly under scenarios D60 and D80. Figure 5.7 explains why this does not affect total cost noticeably: nuclear and wind have very similar cost curves.

![Graph showing total capacity by technology](image)

Figure 5.8: NLP results: Final capacity

Note that the three-stage decision under uncertainty with recourse and continuous sampling of scenarios, as implemented using the ADP model, would not be computationally tractable using conventional LP or NLP solvers. A
similar quality check can therefore not be easily reproduced for the stochastic scenarios discussed in the following sections.

5.2 Introducing regulatory uncertainty

The scenarios of group REG, which model regulatory uncertainty, assume that a carbon cap is introduced after 10, 20, or 50 years (see Table 5.6). The evolution of the cap is modeled as a log normal random walk with a mean of 60% and a range between 20% and 100%. No market uncertainty is assumed.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R10</td>
<td>fixed after year 10, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>R20</td>
<td>fixed after year 20, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
<tr>
<td>R50</td>
<td>fixed after year 50, $\mu = 60%$</td>
<td>fixed</td>
<td>fixed</td>
</tr>
</tbody>
</table>

Table 5.6: Scenarios with regulatory uncertainty (REG)

5.2.1 Total cost and emissions

Table 5.7 shows the total cost and emissions under the scenarios of group REG. The results for scenario D60 are included as a point of reference.

All results are based on learning over 30,000 sample runs.

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>D60</td>
<td>164.3</td>
<td>2.0</td>
</tr>
<tr>
<td>R10</td>
<td>209.1</td>
<td>65.2</td>
</tr>
<tr>
<td>R20</td>
<td>222.6</td>
<td>106.8</td>
</tr>
<tr>
<td>R50</td>
<td>244.9</td>
<td>146.8</td>
</tr>
</tbody>
</table>

Table 5.7: Total cost and emissions

Regulatory uncertainty increases the average cost substantially. In spite of identical mean values for the final cap of 60%, uncertainty during the first ten years (scenario R10) leads to an increase of total cost of 27% on average with only slightly lower average emissions, compared to the deterministic scenario D60.

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More striking, R10 produces higher average costs (+14%) and much higher average emissions (+46%) than the more restrictive deterministic scenario D40. As regulatory uncertainty extends to 20 years (scenario R20) costs are comparable to those of the strictest deterministic scenario D20. Finally, if regulatory uncertainty is only resolved after 50 years (scenario R50), average costs exceed those of D20 by 11% (compare Table 5.2).

Figure 5.9 presents a breakdown by cost component. It shows that particularly capital costs and penalties increase with extended regulatory uncertainty. Penalties can arise from either (i) suboptimal solutions (due to the approximate nature of the optimization methodology used), or (ii) from the optimal strategy that incurs penalties rather than higher capital costs in the event of stringent caps.

![Figure 5.9: Total cost – mean value](image)

Figure 5.10 shows the relationship between total costs and the final carbon cap. If the final realized carbon cap is close to the expected value of 60%, the total costs are similar across all three scenarios. However, for both more and less restrictive caps, total costs of the expansion strategies increase with prolonged regulatory uncertainty.

---

3The graph shows average total NPV per carbon cap range [20%,30%], ..., [90%,100%].
It is important to note that the carbon penalty introduces an asymmetric risk/reward profile: the cost impact from exceeding the carbon cap, typically for more restrictive caps than expected, is greater than the cost of a suboptimal, compliant capacity mix under a less restrictive cap. This asymmetry in costs leads to an optimal hedging strategy that tends to over-comply under uncertainty in the cap.

![Graph showing total cost by final carbon cap](image)

Figure 5.10: Total cost by final carbon cap

### 5.2.2 Capacity expansion

Figure 5.11 and Table 5.8 present the average final capacity mix.

As in the case of the deterministic scenarios, nuclear and the two gas-fired technologies dominate the technology mix under all scenarios. However, in comparison to scenario D60, the contribution from nuclear is significantly lower under R10 and R20 and only reaches similar levels under R50 (see section 5.2.4 for further analysis).

The contribution from the emerging technologies wind, solar, and coal CCS increases with the duration of the regulatory uncertainty, from 0.2% to 3.7% (wind), from 0.2% to 3.6% (solar), and from 0% to 3.5% (coal CCS).
Figure 5.11: Final capacity

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D60</td>
<td>37.0%</td>
<td>0.2%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>39.2%</td>
<td>23.4%</td>
<td>0.0%</td>
</tr>
<tr>
<td>R10</td>
<td>24.7%</td>
<td>2.0%</td>
<td>1.1%</td>
<td>0.6%</td>
<td>46.5%</td>
<td>24.1%</td>
<td>1.0%</td>
</tr>
<tr>
<td>R20</td>
<td>21.6%</td>
<td>2.5%</td>
<td>1.4%</td>
<td>1.8%</td>
<td>39.6%</td>
<td>31.7%</td>
<td>1.4%</td>
</tr>
<tr>
<td>R50</td>
<td>30.7%</td>
<td>3.7%</td>
<td>3.6%</td>
<td>3.5%</td>
<td>29.6%</td>
<td>26.4%</td>
<td>2.4%</td>
</tr>
</tbody>
</table>

Table 5.8: Final capacity – contribution by technology
5.2.3 Production

Figure 5.12 and Table 5.9 present each technology’s contribution to total production.

![Figure 5.12: Total production across all periods](image)

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D60</td>
<td>38.1%</td>
<td>3.1%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>49.0%</td>
<td>2.9%</td>
<td>6.6%</td>
</tr>
<tr>
<td>R10</td>
<td>32.8%</td>
<td>9.1%</td>
<td>0.5%</td>
<td>0.2%</td>
<td>50.9%</td>
<td>1.8%</td>
<td>4.7%</td>
</tr>
<tr>
<td>R20</td>
<td>33.7%</td>
<td>10.9%</td>
<td>0.7%</td>
<td>1.9%</td>
<td>45.1%</td>
<td>2.9%</td>
<td>4.8%</td>
</tr>
<tr>
<td>R50</td>
<td>40.7%</td>
<td>13.9%</td>
<td>1.6%</td>
<td>2.4%</td>
<td>34.0%</td>
<td>1.6%</td>
<td>5.8%</td>
</tr>
</tbody>
</table>

Table 5.9: Total production – contribution by technology

Similar to the final capacity mix, total production is dominated by nuclear and gas. However, the contribution from coal (mostly legacy assets) under all scenarios is more pronounced. The same holds true for wind, particularly as uncertainty remains unresolved for longer.

Most importantly, the contribution from all non-carbon emitting technologies
5.2.4 "Here and now" versus "wait and see" decisions in the case of nuclear

The nuclear expansion pattern (Figure 5.13) across scenarios illustrates the two generic decision making modes of sequential decision making under uncertainty:

1. While uncertainty remains unresolved, investment decisions vary very little across samples, and the decisions typically contain a hedging component to guarantee beneficial results under a wide range of potential final carbon caps (also referred to as "here and now" decisions in the literature).

2. Once uncertainty is removed, expansion decisions vary widely to adjust the capacity mix to the specific carbon cap under a given sample (also referred to as "wait and see" decisions in the literature).

As the lowest-cost non-carbon technology, investment in nuclear generation is chosen to keep the carbon stock as close to the final carbon cap as possible.

As expected, variability with respect to nuclear investments is widest under R10, since two of the three investment decisions occur after uncertainty is eliminated (in years 10 and 20). This reduces the degree of hedging in the first stage decision and allows investment in nuclear capacity to be postponed to the final decision period (which is favorable given the high capital costs of nuclear and a discount rate of 10%). This last build decision, however, varies widely across different samples to adjust to each specific carbon cap sampled.

In contrast, only one investment decision is taken after uncertainty is removed under scenario R20. In this case, the optimal strategy is to expand nuclear capacity sooner to hedge against the risk of tight final carbon caps. The resulting capacity mix reduces the need to react strongly to different states of the stochastic carbon cap process during the final investment decision and thereby reduces variability. Note that, while average final nuclear capacity is lower under R20 than under R10, nuclear contributes slightly more to total production under R20 since expansion in nuclear has begun earlier than under R10 (compare Tables 5.8 and 5.9).
In the case of R50, all investment decisions are made under uncertainty. Decisions are therefore primarily "here and now" decisions and need to provide a sufficient hedge against potentially strict regulatory environments. This explains the higher average final nuclear capacity under R50, compared to R10 and R20. Variability is similar to that of R20.

Figures 5.14 and 5.15 show final capacity and total production under R20 as a function of the final carbon cap.

When there is uncertainty and recourse in investment, nuclear capacity is adapted to different final carbon caps, leading to the variability shown in the box plot of Figure 5.13. Note that even for the least restrictive caps, nuclear capacity never reaches zero.

Wind also fulfills a function similar to that of nuclear, but to a lesser extent because of its intermittent nature (see section 5.2.7 for details).

---

4 Note that the intermediate states of the stochastic carbon cap carry information about the distribution of the final carbon cap. However, information content under R50 is limited at year 20, given the cap is fixed only after another 30 years.
Figure 5.14: Scenario R20 – Final capacity in relation to final carbon cap

Figure 5.15: Scenario R20 – Total production in relation to final carbon cap
Figure 5.16 shows the second stage investment decision (after year 10) as a function of the intermediate carbon cap observed after year 10.

The figure demonstrates how the second-stage decision is affected by the intermediate state values of the stochastic carbon cap process. Although the cap is not fixed until year 20, there is a clear correlation between the (intermediate) value of the carbon cap observed at the end of year 10 and the investment decision at that time. The nuclear capacity added in the second stage ranges from up to 25 GW for the most restrictive intermediate caps to less than 10 GW for the least restrictive. This behavior is rational given that the likelihood of very restrictive final caps after year 20 is low if loose intermediate caps are observed after year 10, and vice versa (see also section 3.3.3).

Such behavior is only apparent in a multi-stage problem framework.
5.2.5 Compliance with carbon policy

This section explores how the length of regulatory uncertainty affects compliance with the imposed carbon policy.

Under scenario R10, the second and third-stage investment decisions are made under perfect information. The two recourse decisions provide sufficient flexibility to comply with the most restrictive caps and to exploit the least restrictive caps fully (see Figure 5.17). Smaller gaps between stock and cap originate purely from the approximate nature of the algorithm, and more sample runs would yield a closer tracking.

![INDIVIDUAL SCENARIOS: TOTAL EMISSIONS VS FINAL CAP R10](image)

Figure 5.17: Scenario 10Y – compliance with cap

Under scenario R20, the second expansion decision is taken under partial uncertainty (it uses the information content of the state value of the random carbon cap—see figure 5.16), and only the last expansion decision is taken with full knowledge of the final cap. For most possible caps, the amount of information provided is sufficient to allow for a close tracking (see Figure 5.18). However, for very restrictive caps between 20% and c. 35%, the optimal expansion strategy leads to non-compliance. This is due to the fact that the alternative strategy of complying with the full range of caps
would have required a more conservative hedging strategy during the first two expansion steps. On an average net present value basis, the additional cost for that strategy would have been higher than the cost for the actual penalties incurred at the restrictive end of the range of caps. Similarly, the model results do not track the least restrictive caps as closely as under scenario R10. To exploit these caps better, a more aggressive expansion strategy during the first build decision would have been required. Such a strategy would have, however, yielded higher and more frequent breaches of restrictive carbon caps, which in turn would have eliminated the gains from better exploiting generous caps.

Finally, Figure 5.19 documents the compliance behavior under R50. Under this scenario, all expansion decisions are taken under uncertainty. Given the prohibitively high carbon penalties, it adopts a conservative strategy that produces a relatively low carbon stock across the entire spectrum of final carbon caps. The strategy is compliant under policies with carbon caps of c. 40% and higher. The carbon stock is slightly upward sloping, driven by the (limited) information content provided by the state value of the stochastic carbon cap at year 20.
Figure 5.19: Scenario 50Y – compliance with cap

Table 5.10 summarizes the results above in the form of four key metrics.\(^5\)

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{Config} & \text{Cap Avg (BNt)} & \text{Stock Avg (BNt)} & \text{Overshoot Avg (\%)} & \text{Undershoot Avg (\%)} \\
\hline
\text{D60} & 5.58 & 5.51 & +0.4\% & -1.3\% \\
\text{R10} & 5.58 & 5.36 & +6.9\% & -6.0\% \\
\text{R20} & 5.71 & 5.22 & +13.3\% & -10.5\% \\
\text{R50} & 5.55 & 4.18 & +25.3\% & -27.2\% \\
\hline
\end{array}
\]

Table 5.10: Compliance with carbon cap – key metrics

\(^5\)"Overshoot Avg" measures the average gap between stock and cap across all samples that resulted in a breach; "Undershoot Avg" measures the average gap across all samples that resulted in policy compliance.
5.2.6 The cost of regulatory uncertainty

A comparison between the results under the deterministic scenarios of group DET with those under the regulatory-uncertainty scenarios of group REG provides an estimate of the cost of hedging required under regulatory uncertainty.

Figure 5.20 shows the average cost as a function of the final carbon cap (grouped in 5% intervals) for all three scenarios of group REG against a benchmark deterministic cost curve DET. The benchmark curve is constructed as the piecewise linear function spanning the emissions/cost points of the five deterministic scenarios DET20 – DET100 (see Table 5.2).

![Cost of Regulatory Uncertainty](image)

Figure 5.20: Cost of regulatory uncertainty, grouped by carbon cap

The graph shows that total costs of the optimal strategies under all three scenarios of group REG consistently exceed the deterministic benchmark. All strategies minimize the cost differential at or close to the expected carbon cap value of 60%. At stricter caps, the difference grows rapidly, driven both by penalties and higher capital costs originating from cleaner setups (more nuclear and wind). As expected, the cost of regulatory uncertainty increases with the length of uncertainty, which is particularly pronounced for strict
policy settings.

A more precise quantification of the cost of regulatory uncertainty is possible by using interpolated values from the benchmark curve to calculate cost deltas for all individual samples (shown for R10 in Figure 5.21) and then averaging these values across all samples.

![Cost of Regulatory Uncertainty - R10](image)

Figure 5.21: Cost of regulatory uncertainty

These averages are presented in Table 5.11. The figures show that total costs increase by up to 45.3% (under R50). If uncertainty is resolved after 10 years (R10), costs still increase by 23.9%.

Note that the table provides a breakdown by cost type: part of the total cost of regulatory uncertainty originates from the average incurred carbon penalty. While the penalty should be considered part of the expansion strategy and thus a normal cost component under scenarios R50 and partly R20, it is likely that under scenario R10, further training of the algorithm would lead to lower average penalties. The non-penalty related cost differential ($17.6 BN, or 10.5% above the benchmark deterministic cost) therefore provides a lower bound for the "fully-converged" cost of regulatory uncertainty under R10.
### Table 5.11: Average cost of regulatory uncertainty

<table>
<thead>
<tr>
<th>Config</th>
<th>Total (BN$)</th>
<th>O/w non-penalty (BN$)</th>
<th>O/w penalty (BN$)</th>
<th>Total in % of avg. det. cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R10</td>
<td>40.4</td>
<td>17.6</td>
<td>22.8</td>
<td>23.9%</td>
</tr>
<tr>
<td>R20</td>
<td>55.1</td>
<td>22.6</td>
<td>32.5</td>
<td>32.9%</td>
</tr>
<tr>
<td>R50</td>
<td>76.4</td>
<td>31.5</td>
<td>44.9</td>
<td>45.3%</td>
</tr>
</tbody>
</table>

#### 5.2.7 The role of wind in restrictive regulatory settings

The amount of final wind capacity strongly correlates with the final carbon cap (see Figure 5.22).

![Figure 5.22: Final nominal capacity as a function of the final carbon cap](image)

For the most restrictive carbon caps, wind contributes approximately half of the final nominal capacity. In contrast, virtually no wind capacity is being built when carbon caps are not constraining. This pattern differs from the expansion pattern for all other technologies which either (i) do not attract investments of a meaningful size, regardless of the carbon cap (solar and
coal), or which (ii) contribute materially to the capacity mix for all observed regulatory regimes (nuclear and gas).

This section explains the specific role of wind in the overall portfolio of available technologies.

The primary reason for investments in new wind capacity (mostly in the last build) is to mitigate potential carbon penalties when breaches of the final carbon cap are likely. This is related to the specific expansion rules and the output profile of a wind farm in the ERCOT region.

Expansion in each period is strictly constrained by the demand during that period: firstly, peak demand plus a small safety margin (set to 1% in all scenarios) needs to be met at all times; secondly, capacity during peak demand hours cannot grow beyond peak demand\(^6\).

In situations where it is foreseeable that the final carbon stock might exceed the final carbon cap, resulting in a potentially very high penalty, the optimal strategy triggers a very large investment in clean generation capacity. However, investment is constrained by the rule that total output during peak demand cannot exceed demand.

In such a setting, wind becomes the most attractive option due to the negative correlation of output and demand (see section 3.3.6): one 100 MW standard size wind farm in the ERCOT region delivers an average output of only 11.8 MW during peak demand hours, but 33.8 MW across all load blocks.

Therefore, a wind-only expansion decision during period 3, in which peak demand grows by 22 GW over the previous period, would require \(22,000 / 11.8 \times 1,864\) standard size wind farms and thereby add on average \(1,864 \times 33.8\) MW = 63 GW of clean generation capacity annually. In comparison, a nuclear-only expansion decision for the same period would add 22 GW of clean capacity (given that output is constant across load blocks); and a solar-only expansion decision during period 3 would only add an average 6.9 GW of clean capacity (given that solar output is positively correlated with demand with an average output of 91 MW during peak demand and only 28.6 MW throughout the year for a 150 MW standard size plant).

Consequently, wind is the most attractive expansion option once mitigation of a potential carbon penalty has become a priority: Table 5.12 quantifies

---

\(^6\)Some negligible excess capacity is unavoidable though, given that expansion in each technology is constrained to integer numbers of each technology's standard size plants.
the benefit of this strategy. The table shows the shadow prices for a carbon constrained setting and a sub-optimal decision\textsuperscript{7}. It shows that the existing decision can be most effectively improved by adding more wind at the cost of coal ($246\text{ M}$ cost reduction for the first MW) and explains why wind capacity is added in large volume under strict carbon regimes.

<table>
<thead>
<tr>
<th></th>
<th>-1MW</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Nuclear</td>
<td>Wind</td>
<td>Solar</td>
<td>Coal</td>
<td>CCS</td>
<td>GT</td>
</tr>
<tr>
<td>+1MW Nuclear</td>
<td>-139</td>
<td>-185</td>
<td>-174</td>
<td>-226</td>
<td>-232</td>
<td>-246</td>
</tr>
<tr>
<td>Wind</td>
<td>-139</td>
<td>-185</td>
<td>-174</td>
<td>-226</td>
<td>-232</td>
<td>-246</td>
</tr>
<tr>
<td>Solar</td>
<td>+47</td>
<td>+185</td>
<td>+11</td>
<td>-41</td>
<td>-47</td>
<td>-61</td>
</tr>
<tr>
<td>Coal CCS</td>
<td>+36</td>
<td>+174</td>
<td>-11</td>
<td>+52</td>
<td>-58</td>
<td>-72</td>
</tr>
<tr>
<td>CCGT</td>
<td>+88</td>
<td>+226</td>
<td>+41</td>
<td>+52</td>
<td>-6</td>
<td>-20</td>
</tr>
<tr>
<td>CT</td>
<td>+94</td>
<td>+232</td>
<td>+47</td>
<td>+58</td>
<td>+6</td>
<td>+14</td>
</tr>
<tr>
<td>Coal</td>
<td>+107</td>
<td>+246</td>
<td>+61</td>
<td>+72</td>
<td>+20</td>
<td>+14</td>
</tr>
</tbody>
</table>

Table 5.12: Shadow prices for a carbon constrained sample ($\text{M}$)

However, wind is not always the most attractive option. A breakdown of the shadow prices by cost components (Table 5.13) gives further insight and explains why wind is not being built when carbon caps do not present a constraint\textsuperscript{8}.

Whenever carbon caps are not constraining, the impact of an expansion decision on emissions becomes irrelevant (the penalty will be zero). In such a scenario, only the sum of capital costs, fixed costs and variable costs (column "Sub-total") become important. However, wind is the most expensive technology by this measure. This explains why no wind capacity is being added whenever it is foreseeable that the final carbon cap will not present a constraint\textsuperscript{9}.

\textsuperscript{7}The shadow price is defined as adding 1 MW of output during peak demand in one technology and subtracting 1 MW of output during peak demand in a second technology. Numbers are based on a sample under scenario R20 which resulted in a final carbon cap of 3 Gt and a final carbon stock of 3.3 Gt; the last, sub-optimal build decision comprised 9 nuclear, 2 coal, 1 coal CCS, 20 CCGT, 48 CT, 607 wind, 7 solar plants.

\textsuperscript{8}The table shows the impact of adding 1 MW of capacity during peak demand in each technology on each cost component without the offsetting capacity reduction in a second technology. The results shown in Table 5.12 can be approximated taking the information of Table 5.13. Example: the impact of replacing 1 MW of coal with 1 MW of wind is approximately $-246.1\text{ M} = -231.9\text{ M} + 14.2\text{ M}$.

\textsuperscript{9}Note that the table only shows shadow prices for a given capacity mix and expansion decision for period 3. Variable costs will be different for other setups. However, capital
To further confirm this observation, Figure 5.23 shows nominal wind capacity added in the last period as a function of the ratio of final cap to carbon stock at the end of year 20.

The solver builds meaningful wind capacity only for ratios of approximately 3.0 and below. This can be explained by the underlying demand profile: demand increases by 2% in the first 30 years and stays constant thereafter; this generates total demand over 50 years of 3.1 times the demand over the first 20 years. Assuming an unchanged capacity mix and dispatch strategy, the total carbon stock after year 50 should therefore equal approximately 3.1 times the carbon stock after year 20. Whenever the carbon cap is therefore fixed (after year 20 in scenario R20) at or above 3.1 times the carbon stock after year 20, it is realistic to assume that a breach of the cap can be avoided by continuing with the previous expansion strategy. However, if the ratio of cap to stock is lower than 3.1, additional wind capacity is required to make the total mix cleaner and to reduce total emissions.

### 5.2.8 Summary of key findings under regulatory uncertainty

In summary, the model results under regulatory uncertainty provide a first estimate of the cost of regulatory uncertainty and the differentiated use of technologies resulting from a multi-stage problem formulation.

The results also demonstrate the importance of incrementally acquired, but costs and fixed costs will not change and will still dominate total cost before penalty. The statement made above will therefore remain valid under different setups.
preaminary information about the state of the system—in this case regulatory guidance—for the optimal decision strategy.

5.3 Introducing market uncertainty

Scenarios D20M to D100M introduce market uncertainty with regards to (i) the price of natural gas, and (ii) the construction cost for emerging technologies. The regulatory parameters under the five scenarios are assumed deterministic with caps ranging from 20% (D20M) to 100% (D100M) of the unconstrained quantity.

The gas price follows a log normally distributed random walk with a drift and an expected value of $11.4 M/MMBtu at the end of year 50, as opposed to a fixed price of $4/MMBtu for the previously analyzed scenarios of groups DET and REG (see section 3.3.4 for further detail).

For the emerging technologies wind, solar, and coal CCS, a decrease in capital cost of 20% per each doubling of the installed base from technological
learning is assumed. The installed legacy base consists of one coal CCS plant, 470 wind plants, and one solar plant\textsuperscript{10}. Prices cannot fall below the capitals cost of a conventional coal plant in the case of coal CCS and below 50\% of the respective initial capital costs in the case of wind and solar. (see section 3.3.5 for further detail).

<table>
<thead>
<tr>
<th>Name</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20M</td>
<td>fixed at 20%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
<tr>
<td>D40M</td>
<td>fixed at 40%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
<tr>
<td>D60M</td>
<td>fixed at 60%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
<tr>
<td>D80M</td>
<td>fixed at 80%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
<tr>
<td>D100M</td>
<td>fixed at 100%</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 5.14: Scenarios with market uncertainty (group MKT)

In the following sections, results will be compared with the results under the corresponding scenarios of group DET to quantify the effect of market uncertainty.

5.3.1 Total cost and emissions

Figure 5.24 and Table 5.15 present the total costs and emissions under the five scenarios of group MKT.

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>D20M</td>
<td>225.9</td>
<td>8.2</td>
</tr>
<tr>
<td>D40M</td>
<td>198.0</td>
<td>13.4</td>
</tr>
<tr>
<td>D60M</td>
<td>192.5</td>
<td>15.8</td>
</tr>
<tr>
<td>D80M</td>
<td>184.9</td>
<td>19.7</td>
</tr>
<tr>
<td>D100M</td>
<td>178.3</td>
<td>21.7</td>
</tr>
</tbody>
</table>

Table 5.15: Market uncertainty scenarios MKT – total cost and emissions

Total costs exceed those under the corresponding deterministic scenarios by between $5M (\pm 2\%) and $31M (\pm 21\%) (see Figure 5.25 and compare Table 5.2), driven by higher average gas prices. As the carbon cap becomes less

\textsuperscript{10}For wind and solar, this reflects the currently installed assets in the ERCOT region; for coal CCS, one plant is assumed as *seed value*. 

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restrictive, the cost gap widens, in line with the growing contribution of gas-fired generators to total production.

5.3.2 Capacity expansion and production

Market uncertainty materially influences the capacity mix under the optimal investment strategy. Figure 5.26 gives an overview of the final results for all five scenarios of group MKT.

A comparison by capacity mix (Table 5.16) and total production (Table 5.17) for the extreme cases of groups DET and MKT shows the influence of both lower capital costs for emerging technologies and higher gas prices under market uncertainty: in all cases, gas is both deployed and dispatched less under market uncertainty, and solar has a more prominent role, particularly under the strictest carbon cap of 20%\(^1\).

\(^1\)Note that table 5.16 shows contribution during the peak demand load block. Given that solar output is positively correlated with demand, contribution of solar to total production is materially lower than its share of peak capacity.
Figure 5.25: Comparison of total NPV, groups DET and MKT

Figure 5.26: Final-stage capacity at peak demand
### Table 5.16: Final capacity – contribution by technology, DET vs. MKT

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>61.4%</td>
<td>0.3%</td>
<td>0.5%</td>
<td>0.4%</td>
<td>22.8%</td>
<td>14.6%</td>
<td>0.1%</td>
</tr>
<tr>
<td>D20M</td>
<td>48.5%</td>
<td>0.2%</td>
<td>24.3%</td>
<td>0.3%</td>
<td>16.6%</td>
<td>10.1%</td>
<td>0.1%</td>
</tr>
<tr>
<td>D100</td>
<td>0.0%</td>
<td>0.1%</td>
<td>0.2%</td>
<td>0.0%</td>
<td>65.1%</td>
<td>34.1%</td>
<td>0.4%</td>
</tr>
<tr>
<td>D100M</td>
<td>2.2%</td>
<td>0.4%</td>
<td>1.6%</td>
<td>1.6%</td>
<td>58.4%</td>
<td>33.4%</td>
<td>2.4%</td>
</tr>
</tbody>
</table>

### Table 5.17: Total production – contribution by technology, DET vs. MKT

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>D20</td>
<td>76.0%</td>
<td>3.1%</td>
<td>0.2%</td>
<td>0.4%</td>
<td>18.4%</td>
<td>1.1%</td>
<td>0.8%</td>
</tr>
<tr>
<td>D20M</td>
<td>69.2%</td>
<td>2.8%</td>
<td>7.1%</td>
<td>0.5%</td>
<td>18.7%</td>
<td>0.9%</td>
<td>1.0%</td>
</tr>
<tr>
<td>D100</td>
<td>3.8%</td>
<td>2.0%</td>
<td>0.1%</td>
<td>0.1%</td>
<td>80.0%</td>
<td>5.5%</td>
<td>8.3%</td>
</tr>
<tr>
<td>D100M</td>
<td>6.1%</td>
<td>3.5%</td>
<td>0.6%</td>
<td>1.9%</td>
<td>72.9%</td>
<td>5.0%</td>
<td>9.9%</td>
</tr>
</tbody>
</table>

### 5.3.3 Influence of specific gas price trajectories on the capacity mix

Figure 5.27 shows the final capacity mix as a function of the final gas price.

While on average, less gas-fired assets are deployed and dispatched under market uncertainty compared to the deterministic scenarios (see above), the differences in capacity mix between low and high gas prices are negligible.

This "averaging" pattern differs from the way the model reacts to different carbon caps under regulatory uncertainty. It is explained by the fact that after year 20, the time of the last capacity expansion decision, (i) 30 out of 50 operating years (and 68% of total demand) are still upcoming, (ii) gas prices remain variable during that time, and (iii) the gas price after year 20 carries insufficient information about the future price distribution.
5.4 Combining regulatory and market uncertainty

Scenario R20M combines regulatory and market uncertainty, assuming an uncertain carbon cap that is fixed after 20 years, stochastic gas prices, and technological learning for solar, wind and coal CCS of 20% per each doubling of the installed base (see Table 5.18).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon cap</th>
<th>Gas price</th>
<th>Capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>fixed after year 20, $\mu = 60%$</td>
<td>variable</td>
<td>variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 5.18: Scenario with regulatory and market uncertainty (R20M)

Results are compared with those of the two corresponding baseline scenarios R20 (regulatory uncertainty only) and D60M (market uncertainty only).

The higher dimensionality of R20M results in slower convergence. To achieve similar convergence as in the case of the baseline scenarios, the results for
R20M discussed here are based on 40,000 (instead of 30,000) runs.

5.4.1 Total cost and emissions

As expected, total costs under R20M are substantially higher than under both baseline scenarios (see Figure 5.28 and Table 5.19). It is noteworthy that total costs under R20M even exceed those under the strictest market uncertainty scenario D20M by 9% (see Table 5.15).

![Figure 5.28: Total cost – mean value](image)

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>R20</td>
<td>222.6</td>
<td>106.8</td>
</tr>
<tr>
<td>D60M</td>
<td>192.8</td>
<td>16.8</td>
</tr>
<tr>
<td>R20M</td>
<td>246.4</td>
<td>96.5</td>
</tr>
</tbody>
</table>

Table 5.19: Regulatory and market uncertainty scenario R20M – total costs and emissions
5.4.2 Capacity expansion and production

Figure 5.29 and Table 5.20 present the average final capacity under R20M and the two baseline scenarios. Figure 5.30 and Table 5.21 show the corresponding production figures.

Nuclear and gas dominate the capacity mix, but compared to both baseline scenarios, the combination of regulatory uncertainty and market uncertainty also leads to a significant increase in the deployment and dispatch of emerging technologies wind, solar, and coal CCS: clean technologies (including low-carbon coal CCS) contribute 65.5% to total production. Of that, 18.6% originate from wind, solar, and coal CCS. In addition, coal still contributes...
Figure 5.30: Total production across all periods

Table 5.21: Total production – contribution by technology
to a small, but measurable extend to final capacity and even more to total production.

Figure 5.31 presents the final capacity as a function of the final carbon cap. The figure shows that solar and coal CCS contribute across the range of final carbon caps. Expansion in wind however resembles the pattern discussed in section 5.2.7: wind contributes materially when a breach of the final carbon cap seems likely, but it plays only a minor role under less constrained regulatory regimes. Notwithstanding, the contribution of wind to total production on average exceeds the contributions from solar and coal CCS by a wide margin.

Finally, Figure 5.32 compares the first-stage build decisions. The graph shows that the optimal model solution includes considerably more capacity of wind, solar, and coal CCS under R20M than under any of the two baseline scenarios. This increases the benefits from technological learning during the later expansion stages. Note that only the combination of regulatory and market uncertainty creates such behavior.

The first-stage build under R20M also contains a larger proportion of nuclear capacity than under R20. This gap tightens however until the last decision
period: final nuclear capacity under both scenarios is relatively similar (see Table 5.20).

The technology mix under scenario R20M is explained in more detail in the following section 5.4.3.

5.4.3 Using screening curves to explain the final capacity mix

To better understand the optimal investment strategy, consider two sets of screening curves:

Figure 5.33 takes the view of a carbon constrained environment during the last build decision, when the penalty is due in 30 years; it is assumed that technological learning has brought down the capital cost of wind, solar and coal CCS to the respective lower limits, and that gas prices equal the expected final value of $14.4 M/MMBtu.

Figure 5.34 differs from figure 5.33 only in the sense that an unconstrained
policy environment is assumed.

Under R20M, both constrained and unconstrained regulatory regimes are equally likely. Assuming the two sets of screening curves together provide a sufficiently good proxy for the actual cost competitiveness of each technology under both regimes, the final capacity mix should be a blend of the mixes suggested by both set of curves; this suggests a final mix that comprises primarily gas and wind.

The actual expansion strategy however leads to a mix with a higher than expected contribution from nuclear, a lower than expected contribution from wind, and meaningful contributions from all other technologies (see Figure 5.29). The following motivates these differences without attempting to quantify each statement:

1. The assumed legacy mix has a substantial wind component (c. 470 plants of 100 MW nominal capacity each); material investments in new wind capacity are therefore required before the full cost reduction from technological learning materializes\(^{12}\); however, the first rounds of investments do not fully benefit from the final cost saving; this increases
Figure 5.34: Screening curve in an unconstrained policy environment

the actual average cost of wind above the line shown in Figure 5.33.

2. Due to the negative correlation of wind output and demand, expansion in wind requires concurrent build up of excess back up capacity; this is an undesired side effect under unconstrained settings and pushes the cost of wind further above the line shown in the screening curve graphs.

3. The first two arguments in combination explain why wind is more expensive than suggested by the screening curves, and why the model chooses nuclear instead as the primary clean base load technology.

4. Wind has however an important role in mitigating potentially extreme penalties during the last investment decision (see section 5.2.7 for a detailed analysis). This explains why wind contributes substantially to the final capacity mix and total production even though construction in wind has not been large enough to create the full benefits from technological learning.

\[12\] To achieve the maximum of 50% cost saving, the installed wind base would need to double 2.5 times; accordingly the required new capacity amounts to \[2^{2.5} \times 470 - 470 = 2189\] plants of 100 MW nominal capacity each.
5. Since wind is not competitive in an unconstrained policy setting, Figure 5.34 suggests that coal should take its role as base load technology; the model results reflect this, however not to the extent the graph suggests; the optimal solution includes a substantial investment in nuclear as a hedge in the first period; this capacity is available in the succeeding periods at very low variable operating costs; as a consequence, coal is deployed in an unconstrained policy setting only to the extend early-stage nuclear investments are not sufficient to satisfy the base load demand (above c. 4,800 hours of operation).

6. Figure 5.33, corrected for higher wind costs, also explains why a limited amount of coal CCS is being deployed: it serves as medium-load technology between gas and nuclear under constrained policy settings; this again assumes that cost savings from technological learning can be fully utilized, but this is possible without much less initial investments than in the case of wind, since the legacy portfolio contains only one coal CCS plant\textsuperscript{13}.

7. Finally, the screening curves suggest that solar should be uncompetitive in both constrained and unconstrained policy settings; the actual mix however includes meaningful solar capacity; the main driver behind this effect is the fact that solar output positively correlates with demand; each 1 MW of average output across a year from solar satisfies approximately 3 MW of peak demand; assuming full cost reductions from technological learning, solar becomes attractive because of that feature as a niche peak load provider (replacing CT) in constrained policy environments with high gas prices; early-stage investments decrease capital costs by the maximum amount of 50\% as a result of technological learning (the legacy installed base in solar is small).

5.4.4 Compliance with carbon policy

Figure 5.35 and Table 5.22 show the level of compliance with different final caps under the optimal investment strategy.

The figure shows that the strategy adjusts reasonably well to carbon caps from c. 30\% up to the expected value of 60\%. For more restrictive caps, the strategy is typically non-compliant and for less restrictive caps over-
\textsuperscript{13}Note however, that section 5.5 will show that a no-coal expansion strategy can perform slightly better than the strategy discussed here.
<table>
<thead>
<tr>
<th>Config</th>
<th>Cap Avg (BNt)</th>
<th>Stock Avg (BNt)</th>
<th>Overshoot Avg (%)</th>
<th>Undershoot Avg (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20</td>
<td>5.71</td>
<td>5.22</td>
<td>+13.3%</td>
<td>-10.5%</td>
</tr>
<tr>
<td>D60M20</td>
<td>5.58</td>
<td>5.38</td>
<td>+0.9%</td>
<td>-3.7%</td>
</tr>
<tr>
<td>R20M20</td>
<td>5.62</td>
<td>4.75</td>
<td>+14.9%</td>
<td>-17.1%</td>
</tr>
</tbody>
</table>

Table 5.22: Compliance with carbon cap – key metrics

![Graph showing individual scenarios: total emissions vs final cap R20M](image)

Figure 5.35: Compliance with carbon cap, R20M
compliant. This is due to the high level of uncertainty and the resulting need for early-stage hedging under R20M. Additionally, driven by the benefits from technological learning, investments in clean technologies are higher during the first stage than is the case in the absence of market uncertainty.

5.4.5 The cost of regulatory uncertainty

Figure 5.36 and Table 5.23 show the cost differential originating from regulatory uncertainty. The approach mirrors the one described in section 5.2.6. The benchmark cost curve is derived from the total costs of the optimal investment strategies under market uncertainty (see Table 5.7).

![Cost of Regulatory Uncertainty Graph]

The average cost of regulatory uncertainty amounts to $53.7 M, or 27.9% of the total costs under fixed regulatory settings. The non-compliance under very restrictive regimes appears to be part of the expansion strategy under R20M. The related penalty costs should therefore be considered an integral part of the cost of regulatory uncertainty (compare Figure 5.35).
Table 5.23: Average cost of regulatory uncertainty

<table>
<thead>
<tr>
<th>Config</th>
<th>Total (BN$)</th>
<th>Cost of regulatory uncertainty</th>
<th>Total in penalty (BN$)</th>
<th>% of avg. det. cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>53.7</td>
<td>24.1</td>
<td>29.6</td>
<td>27.9%</td>
</tr>
</tbody>
</table>

The figure shows that, similar to the results of section 5.2.6, the optimal strategy adapts best to the expected carbon cap of 60%, and differences are largest for very restrictive carbon caps.

5.4.6 The cost of ignoring uncertainty

In a multi-stage decision process, ignoring uncertainty can be interpreted in two different ways:

1. The first-stage decision is based on expected values, and all subsequent decisions are based on an adaptive (ADP-optimized) expansion strategy.

2. All decisions are based on expected values, where expected values at any stage are updated based on the particular values of the stochastic variables per stage and given sample.

The following results are based on the former approach. More specifically, the first-stage decision is fixed and matches the optimal first-stage investment decision under the deterministic scenario D60. The optimal expansion strategy for the remaining two build decisions is then a result of the ADP model under full consideration of the existing uncertainties.

Figure 5.37 shows the differences in the first-stage decisions: under D60, the first-stage investment decision consists exclusively of the two gas technologies CCGT and CT, while under R20M, all technologies contribute (compare section 5.4.3).

In spite of the differences in the first-stage decision, Table 5.24 shows that the difference in expected total costs is less than 1%. However, ignoring uncertainty increases the standard deviation of total costs. This can be explained by the decreased ability to adapt to different carbon caps, which is only partly compensated by a lower average final emissions stock.
Figure 5.37: First-stage build decision

Table 5.24: Cost of ignoring uncertainty – total cost and emissions

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$) $\mu$</th>
<th>Cost (BN$) $\sigma$</th>
<th>Emissions (BNt) $\mu$</th>
<th>Emissions (BNt) $\sigma$</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>246.4</td>
<td>96.5</td>
<td>4.8</td>
<td>0.9</td>
</tr>
<tr>
<td>R20MFIX</td>
<td>248.2</td>
<td>131.4</td>
<td>4.7</td>
<td>0.7</td>
</tr>
</tbody>
</table>
Figure 5.38 provides more detail with respect to the performance of both strategies in relation to the final carbon cap:

1. R20MFI X performs best when the final carbon cap is close to the expected value of 60% due to the fact that under R20MFI X no first-stage hedging costs are incurred and the algorithm is "lucky" in these cases to encounter scenarios that are close to the scenario that the algorithm was trained to optimize.

2. Under more restrictive caps, the optimal investment strategy under R20MFI X does not perform as well as the optimal investment strategy under R20M, given that it is less flexible in its investment strategy (the first-stage decision is fixed and unhedged).

3. Under less restrictive caps, R20MFI X outperforms R20M slightly since it benefits from not having incurred R20M's full (under these scenarios not required) hedging costs against restrictive caps.

Figure 5.38: Total NPV in relation to final carbon cap

Figure 5.39 and Tables 5.25 and 5.26 show that differences in the average capacity mix and production between the two strategies remain until the last stage:
1. Since the optimal investment strategy under R20MFIX did not comprise any investments into technological learning in the first stage, the emerging technologies contribute in total only 6.1% (vs. 9.6% under R20M) to the final capacity mix.

2. Emerging technologies contributed 13% under R20MFIX to total production vs. 18.6% under R20M.

3. R20MFIX over-compensates that gap in clean energy production by building more nuclear capacity.

![Figure 5.39: Final capacity](image)

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>23.1%</td>
<td>2.7%</td>
<td>3.6%</td>
<td>3.3%</td>
<td>40.0%</td>
<td>25.4%</td>
<td>1.6%</td>
</tr>
<tr>
<td>R20MFIX</td>
<td>28.3%</td>
<td>2.1%</td>
<td>1.7%</td>
<td>2.3%</td>
<td>29.8%</td>
<td>34.2%</td>
<td>1.5%</td>
</tr>
</tbody>
</table>

Table 5.25: Final capacity – contribution by technology

Finally, Table 5.27 and Figure 5.40 confirm that R20MFIX is disadvantaged in its ability to adapt to the final carbon cap: the results under R20MFIX
Table 5.26: Total production – contribution by technology

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>37.9%</td>
<td>12.7%</td>
<td>1.6%</td>
<td>4.3%</td>
<td>34.0%</td>
<td>1.6%</td>
<td>7.8%</td>
</tr>
<tr>
<td>R20MFIX</td>
<td>44.7%</td>
<td>9.6%</td>
<td>0.6%</td>
<td>2.8%</td>
<td>31.4%</td>
<td>3.7%</td>
<td>7.1%</td>
</tr>
</tbody>
</table>

show a larger extent of both non-compliance and over-compliance than the results under R20M (compare with Table 5.22).

Figure 5.40: Compliance with carbon cap - R20MFIX

5.4.7 Summary of key findings under regulatory and market uncertainty

In summary, the results show that regulatory uncertainty triggers substantial hedging activity under the optimal investment strategy. This changes the shape of the technology mix chosen during the early-stage investment decisions and increases total costs materially. Total costs incurred under regulatory and market uncertainty (R20M) exceed the total costs incurred
<table>
<thead>
<tr>
<th>Config</th>
<th>Cap Avg (BNt)</th>
<th>Stock Avg (BNt)</th>
<th>Overshoot Avg (%)</th>
<th>Undershoot Avg (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>5.62</td>
<td>4.75</td>
<td>+14.9%</td>
<td>−17.1%</td>
</tr>
<tr>
<td>R20MFIX</td>
<td>5.65</td>
<td>4.71</td>
<td>+18.3%</td>
<td>−19.8%</td>
</tr>
</tbody>
</table>

Table 5.27: Compliance with carbon cap – key metrics

even under the strictest (deterministic) regulatory regime and under market uncertainty (D20M) by $20.5 M, or 9%.

Ignoring uncertainty during the first-stage investment decision results in structural differences that remain until the final stage. Average costs are similar under R20M and R20MFIX. However, the optimal investment strategy under R20M is able to react more flexibly to a wide range of regulatory environments.

5.5 Exclusion of technologies

This section analyzes scenarios where one or more technologies are excluded from the portfolio of technologies available for construction\textsuperscript{14}, specifically: nuclear, coal + coal CCS, and a combination of all three technologies (see Table 5.28).

Exclusions in reality could be the result of technology-specific, prescriptive policies, or of a lack of support for the development of new technologies.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Technology exclusion</th>
<th>Carbon cap</th>
<th>Gas price and capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>TnR20M</td>
<td>nuclear</td>
<td>fixed year 20, (\mu = 60%)</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TccR20M</td>
<td>coal</td>
<td>fixed year 20, (\mu = 60%)</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TnccR20M</td>
<td>nuclear + coal</td>
<td>fixed year 20, (\mu = 60%)</td>
<td>all variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 5.28: Scenarios with technology exclusion (group T)

\textsuperscript{14}Note that the legacy portfolio is not impacted by an exclusion.
The analysis focuses on the cost impact of technology exclusion and the differences of the resulting strategies compared to the optimal investment strategy under the equivalent, all-technology baseline scenario R20M.

The final part of this section will evaluate the cost of regulatory uncertainty under technology exclusion.

### 5.5.1 Total cost and emissions

Figure 5.41 and Table 5.29 show the total costs and emissions under all three scenarios.

Surprisingly, technology exclusion does not impact total costs significantly under any of the three scenarios. In the case of coal exclusion (TccR20M), costs of the resulting expansion strategy are even 2% lower than under the benchmark scenario R20M.

![Figure 5.41: Total cost – mean value](image)
5.5.2 Capacity expansion and total production

Figures 5.42 and 5.43 and Tables 5.30 and 5.31 show the final capacity mixes and production profiles under each of the three exclusion scenarios.

Whenever nuclear is excluded, a combination of the three emerging technologies is used as a substitute. Whenever the two coal technologies are excluded, they are substituted by a mix of primarily solar, and secondarily wind and gas.

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>R20M</td>
<td>246.4</td>
<td>96.5</td>
</tr>
<tr>
<td>TnR20M</td>
<td>249.2</td>
<td>94.9</td>
</tr>
<tr>
<td>TccR20M</td>
<td>240.3</td>
<td>103.6</td>
</tr>
<tr>
<td>TnccR20M</td>
<td>252.7</td>
<td>122.5</td>
</tr>
</tbody>
</table>

Table 5.29: Excluding technologies (T) – total cost and emissions

![Figure 5.42: Final capacity](image)

To understand these expansion strategies, it is worth going back to the
Table 5.30: Final capacity – contribution by technology

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M20</td>
<td>23.0%</td>
<td>2.7%</td>
<td>3.6%</td>
<td>3.3%</td>
<td>40.0%</td>
<td>25.4%</td>
<td>1.6%</td>
</tr>
<tr>
<td>TnR20M</td>
<td>0.0%</td>
<td>8.1%</td>
<td>11.3%</td>
<td>10.7%</td>
<td>35.4%</td>
<td>31.5%</td>
<td>3.0%</td>
</tr>
<tr>
<td>TcR20M</td>
<td>20.3%</td>
<td>3.8%</td>
<td>6.4%</td>
<td>0.0%</td>
<td>33.0%</td>
<td>36.4%</td>
<td>0.0%</td>
</tr>
<tr>
<td>TncR20M</td>
<td>0.0%</td>
<td>10.2%</td>
<td>15.9%</td>
<td>0.0%</td>
<td>44.3%</td>
<td>29.6%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

Table 5.31: Total production – contribution by technology

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M20</td>
<td>37.9%</td>
<td>12.7%</td>
<td>1.6%</td>
<td>4.3%</td>
<td>34.0%</td>
<td>1.6%</td>
<td>7.8%</td>
</tr>
<tr>
<td>TnR20M</td>
<td>3.8%</td>
<td>31.3%</td>
<td>4.8%</td>
<td>14.3%</td>
<td>39.9%</td>
<td>2.7%</td>
<td>3.2%</td>
</tr>
<tr>
<td>TcR20M</td>
<td>31.4%</td>
<td>16.0%</td>
<td>2.7%</td>
<td>0.2%</td>
<td>41.0%</td>
<td>3.9%</td>
<td>4.8%</td>
</tr>
<tr>
<td>TncR20M</td>
<td>3.8%</td>
<td>35.6%</td>
<td>6.9%</td>
<td>0.2%</td>
<td>47.8%</td>
<td>1.9%</td>
<td>3.8%</td>
</tr>
</tbody>
</table>

Figure 5.43: Total production across all periods
screening curves and arguments introduced in section 5.4.3:

1. Wind is used as the primary substitute for nuclear as clean (albeit intermittent) base load technology under both constrained and unconstrained policy settings. Figures 5.33 and 5.34 clearly demonstrate why wind takes this role. Note that under R20M, nuclear is still slightly more attractive than wind, but after excluding nuclear, wind becomes the most attractive option. Early investments are however required to bring capital cost for wind (via technological learning) down to the levels shown in the screening curve graphs.

2. As under R20M, solar benefits from the fact that its output is positively correlated with demand.

3. Finally, where coal is not excluded (TnR20M), coal CCS is being deployed and dispatched more pronouncedly than under R20M and serves as a medium demand technology which becomes price competitive particularly in constrained policy settings with high gas prices.

4. For all three scenarios, the two gas technologies are dominating both capacity mix and (to a lesser extent) total production.

Figure 5.44 shows the nominal capacity after the final expansion stage under scenario ThcR20M as a function of the final carbon cap. As expected, nominal capacity widely exceeds the peak demand of 119 GW, particularly under more restrictive carbon caps, because of the unusually high level of intermittent resources. The large amount of wind and solar requires considerable backup facilities in the form of the two gas technologies.

It should be noted that in the absence of economic storage options—deployment of wind at the scale shown here (7 to 8 times the currently installed wind base in the ERCOT region) appears ambitious in reality: the large swings in output would create material challenges and costs for the entire infrastructure which are not modeled here. In that context, it is also noteworthy that the extent of intermittence of wind is underestimated by the existing model due to the averaging of wind output across each demand load block (see section 3.3.6).

In addition, the optimal investment strategy results in a technology mix which is highly dependent on the availability and cost of natural gas. Such a strategy might not be desirable economically or politically, given existing uncertainties with respect to the level of available unconventional gas reservoirs in the U.S. and the value of natural gas for applications other than
Figure 5.44: Technology exclusion – final nominal capacity as a function of the final carbon cap, TnccR20M
power generation (e.g., transportation and heating).

### 5.5.3 The cost of regulatory uncertainty

This section develops the cost of regulatory uncertainty for the most restrictive exclusion scenario, TnccR20M.

In order to perform this calculation, a new baseline is introduced which is based on the results under the scenarios introduced in Table 5.32. The total cost under these five baseline scenarios (see Table 5.33) define again a piecewise linear function that serves as a reference cost curve.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Technology exclusion</th>
<th>Carbon cap</th>
<th>Gas price and capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>TnccD20M</td>
<td>nuclear + coal</td>
<td>fixed at 20%</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TnccD40M</td>
<td>nuclear + coal</td>
<td>fixed at 40%</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TnccD60M</td>
<td>nuclear + coal</td>
<td>fixed at 60%</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TnccD80M</td>
<td>nuclear + coal</td>
<td>fixed at 80%</td>
<td>all variable, 20% learning</td>
</tr>
<tr>
<td>TnccD100M</td>
<td>nuclear + coal</td>
<td>fixed at 100%</td>
<td>all variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 5.32: Scenarios with technology exclusion under regulatory certainty (group TD)

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$) μ</th>
<th>Emissions (BNt) μ</th>
<th>σ</th>
<th>σ</th>
</tr>
</thead>
<tbody>
<tr>
<td>TnccD20M</td>
<td>245.2</td>
<td>11.5</td>
<td>1.8</td>
<td>0.0</td>
</tr>
<tr>
<td>TnccD40M</td>
<td>209.4</td>
<td>17.8</td>
<td>3.6</td>
<td>0.1</td>
</tr>
<tr>
<td>TnccD60M</td>
<td>198.0</td>
<td>19.4</td>
<td>5.4</td>
<td>0.2</td>
</tr>
<tr>
<td>TnccD80M</td>
<td>189.4</td>
<td>21.5</td>
<td>7.2</td>
<td>0.3</td>
</tr>
<tr>
<td>TnccD100M</td>
<td>181.5</td>
<td>22.3</td>
<td>8.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 5.33: Technology exclusion under regulatory certainty (TD) - total costs and emissions

Figure 5.45 and Table 5.45 show the results of the calculation. The figure shows good tracking of the deterministic reference curve for caps from c.
60% to 100% (differences of $10 – 20 M). However, non-compliance for more restrictive policy environments drives up the cost of regulatory uncertainty to $52.3 M, or 26.1% of the average reference cost.

Figure 5.45: Technology exclusion – the cost of regulatory uncertainty

<table>
<thead>
<tr>
<th>Config</th>
<th>Total (BN$)</th>
<th>Cost of regulatory uncertainty</th>
<th>% of avg. det. cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>TncR20M</td>
<td>52.3</td>
<td>11.2</td>
<td>26.1%</td>
</tr>
</tbody>
</table>

Table 5.34: Technology exclusion – average cost of regulatory uncertainty

5.5.4 Summary of key findings under technology exclusion

The exclusion of technologies such as nuclear and coal does not necessarily increase total costs. The existence of substitute technologies with comparable cost profiles, such as wind and gas, enables competitive alternative investment strategies.
Such strategies might not be feasible in reality, given the large contribution from intermittent wind generators. In addition, the resulting dependency on natural gas might not be desirable from an economical or political perspective.

However, the analysis shows that, assuming a continued trend of cost reductions through technological learning, wind-powered electricity generation could take a much more pronounced role in the future than it has today.

5.6 Two-stage versus three-stage

This final results section analyzes the differences in strategy if only two investment decisions—at year 0 and after 20 years—are modeled. Two-stage decision processes have been widely used in the research of optimal investment strategies. The following analysis therefore focuses particularly on results that a 3-stage model can produce but a 2-stage model cannot.

Obviously, both 2-stage and 3-stage decision processes are imperfect proxies of a real capacity expansion process over 50 years, which typically consists of yearly incremental investments. However, any differences between 2-stage and 3-stage processes point at potential further insights that could arise from adding further expansion steps.

The two-stage scenario S2R20M analyzed in the following includes both regulatory and market uncertainty identical in parameters to those of scenario R20M (see Table 5.35). Consequently, results will be compared with those under R20M.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Decision stages</th>
<th>Carbon cap</th>
<th>Gas price and capital cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>S2R20M</td>
<td>2 (at $t_0$ and at the end of year 10)</td>
<td>fixed after year 20, $\mu = 60%$</td>
<td>all variable, 20% learning</td>
</tr>
</tbody>
</table>

Table 5.35: Two-stage decision scenario
5.6.1 Total costs and emissions

Figures 5.46 and 5.47 and Table 5.36 compare total costs and emissions.

Both approaches produce virtually identical total average costs. However, the results differ under specific regulatory regimes: the 2-stage approach leads to more conservative solutions and over-compliance under constrained policy environments at the cost of suboptimal solutions under less constrained settings (see Figure 5.47).

Table 5.36 provides further evidence of the more conservative investment strategy resulting from a 2-stage model: total average emissions are considerably lower than under the 3-stage scenario R20M.

<table>
<thead>
<tr>
<th>Config</th>
<th>Cost (BN$)</th>
<th>Emissions (BNt)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\mu$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>R20M</td>
<td>246.4</td>
<td>96.5</td>
</tr>
<tr>
<td>S2R20M</td>
<td>247.0</td>
<td>73.8</td>
</tr>
</tbody>
</table>

Table 5.36: 3-stage vs. 2-stage – total cost and emissions
5.6.2 Capacity expansion total production

The more cautious investment strategy under 2-stage model is also evidenced by the first-stage investment decision (see Figure 5.48): almost half of the capacity expansion at $t_0$ consists of nuclear assets\textsuperscript{15}. At the same time, the model results under S20R20M show less investments in solar and coal CCS over the first 20 years than under R20M over the first 10 years only.

The first-stage decision affects the final capacity mix, which under S2R20M contains more nuclear capacity and considerably less emerging technologies (see Figure 5.49 and Table 5.37). This is a direct consequence of the missing decision stage: technological learning requires early investments into wind, solar, or coal CCS; these investments are too expensive in a 2-stage setting, since they all need to occur at $t_0$; in contrast, R20M allows a phased build up, where the second-stage investment already benefits from technol-

\textsuperscript{15}Note that the first-stage decision under S2R20M covers 20 years instead of 10 years for R20M. Note also that the actual build up following each investment decision is modeled as a yearly process that tracks demand closely in order to avoid an unrealistic amount of excess capacity.
logical learning originating form the first-stage investment. This produces a more realistic, stronger technological learning pattern under R20M, which results in a larger contribution of emerging technologies to the final capacity mix.

Table 5.37: Final capacity - contribution by technology

<table>
<thead>
<tr>
<th>Config</th>
<th>Nuclear</th>
<th>Wind</th>
<th>Solar</th>
<th>Coal CCS</th>
<th>CCGT</th>
<th>CT</th>
<th>Coal</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>23.3%</td>
<td>2.7%</td>
<td>3.6%</td>
<td>3.3%</td>
<td>40.0%</td>
<td>25.4%</td>
<td>1.6%</td>
</tr>
<tr>
<td>S2R20M</td>
<td>29.1%</td>
<td>1.9%</td>
<td>1.4%</td>
<td>1.7%</td>
<td>25.6%</td>
<td>39.0%</td>
<td>1.3%</td>
</tr>
</tbody>
</table>

5.6.3 Compliance with carbon policy

Figure 5.50 (compare Figure 5.35 and Table 5.38) demonstrates again the conservative investment approach resulting from the two-stage problem formulation: because it is geared towards complying with a wide range of possible outcomes and because the process is limited to two decisions, S2R20M
results in a strategy that over-complies under all but the most conservative policy settings.

However, under constrained policy settings, Table 5.38 shows that the 2-stage leads to larger breaches than the 3-stage approach.

<table>
<thead>
<tr>
<th>Config</th>
<th>Cap Avg (BNt)</th>
<th>Stock Avg (BNt)</th>
<th>Overshoot Avg (%)</th>
<th>Undershoot Avg (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>R20M</td>
<td>5.62</td>
<td>4.75</td>
<td>+14.9%</td>
<td>-17.1%</td>
</tr>
<tr>
<td>S2R20M</td>
<td>5.63</td>
<td>3.69</td>
<td>+18.9%</td>
<td>-34.1%</td>
</tr>
</tbody>
</table>

Table 5.38: Compliance with carbon cap – key metrics

5.6.4 Summary of key findings from adding decision stages

The above comparison shows two-stage decision models produce over-conservative investment strategies that are limited in their ability to adapt to different regulatory and market environments.
In addition, two-stage models underestimate the influence of control decisions on future states of the system, as evidenced in the case of technological learning. This creates different incentive structures and thereby sub-optimal investment decisions.

Finally, multi-stage models better reflect the effects of incremental learning based on preliminary information about the system, such as the state values of the preliminary carbon cap after year 10 (see figure 5.16).

The differences between the two-stage and the three-stage problem formulation suggests that a further increase of the number of decision stages might yield even more adaptive and realistic investment strategies.
Chapter 6

Conclusion

This chapter concludes the thesis with a summary of the main findings and suggested future areas of research.

6.1 Major findings

The major results can be summarized in five main statements:

**Regulatory uncertainty leads to substantially higher costs**

Regulatory uncertainty forces decision makers to hedge risks during early stages of the investment process, and such hedging results in substantial sunk costs and suboptimal investment decisions.

This suggests that regulators can positively influence the total cost of electricity production, even while implementing strict environmental standards, by providing certainty about future regulation.

**Decision makers acquire and adapt to new information incrementally**

Two-stage decision formulations of sequential decision making problems typically assume that all uncertainty is removed at a distinct point in time.
and that decision makers react to the new information with a single final investment decision.

In reality, investors receive information—such as guidance by regulators or price updates—incrementally and adapt their investment strategies accordingly. This enables investors to reduce the amount of early-stage hedging and to better adapt to regulatory and market changes.

Multi-stage models are able to simulate such behavior and thereby lead to more realistic and more flexible investment strategies than two-stage models. Multi-stage models also deliver more precise results with respect to the impact of investors’ decisions on the future state of the system, as exemplified by the case of technological learning (see section 5.6).

**Static planning approaches oversimplify technology choices**

Long-term decision making often relies on static forecasts and simple measures such as screening curves. This often leads to inflexible strategies, driven by less diversified first-stage investment decisions.

Multi-stage models that incrementally react to new information and uncertainty tend to result in more diversified first-stage investment decisions. This substantially improves the adaptability of an investment strategy to future system changes (see section 5.4).

**Technological learning strongly impacts optimal investment decision strategies**

The economic viability of new technologies often depends on continued cost reductions originating from technological learning. Technological learning thus has a strong impact on optimal investment strategies.

Multi-stage models are able to capture the full impact of technological learning (see sections 5.2 and 5.4). It should be noted, however, that the model presented in this thesis assumes the existence of a central planner who would have a clear economic interest in investing early in emerging technologies to benefit from technological learning later. In a deregulated market with independent agents, this is not the case. To the contrary, rational agents will only invest in new technologies once they have become economically
attractive. Accordingly, policy makers have an important role in encouraging investments in new technologies via technology-specific measures such as subsidies, and research, development and demonstration (RD&D).

Notwithstanding the assumption of a central planner, multi-stage models, by capturing the positive effects of technological learning, can provide important insight to policy makers with respect to (i) thresholds at which certain technologies become economically viable, and (ii) the amount of potential subsidies required.

6.1.1 Technology exclusion results in investment strategies that are less adaptable to changes, but also provides insight into alternative investment strategies

The model results do not reveal large differences in total costs if base-load technologies, such as nuclear and coal, are excluded. This is driven by substitute technologies, in particular wind and gas, that have cost structures comparable to those of the excluded technologies.

The exclusion of technologies generally reduces the flexibility of the optimal investment strategy. In addition, the amount of deployed wind capacity and the over-reliance on natural gas puts the viability of the investment strategy presented in section 5.5 into question.

However, the model results of section 5.5 provide important insight into alternative investment strategies. In particular, the optimal investment strategies under technology exclusion emphasize the important role that wind can play as a source of electricity in the future.

6.2 Areas of future research

The following model extensions can lead to valuable additional insight:

1. The introduction of further decision stages (e.g., the shorting of investment horizons from 10 years to 5 years) will most likely increase the adaptability of the resulting investment strategies and further improve the modeling of decision dependence (such as technological learning).

2. The introduction of more technologies, in particular hydro power, can improve the applicability of the model to other geographic regions.
3. Utility-size storage capabilities can be simulated to test the influence of storage availability on the attractiveness of intermittent technologies such as wind and solar.

4. Technology-specific capacity limits can make model results more relevant for a specific geographic region.
Appendix A

Economics of generating technologies

Table A.1 – Assumptions and sources

- Biothermal: Carbon content of fuel measured in kg per MWh.
- Carbon capture and sequestration (CCS): Stated carbon content of fuel assumes a capture ratio of 90%.
- Fuel prices ($ per MMBTU): 1.98 coal, 4.0 natural gas, 0.19 nuclear
- Source: [16], except noted below.
- Source nuclear heat rate: [20]
<table>
<thead>
<tr>
<th>Energy source</th>
<th>Technology</th>
<th>Nominal capacity (MW)</th>
<th>Heat rate (MMBTU per MWh)</th>
<th>Capital cost (MM$ per MW)</th>
<th>Fixed O&amp;M cost ($ per MW-year)</th>
<th>Variable O&amp;M cost ($ per MWh)</th>
<th>Variable fuel cost (M$ per MWh)</th>
<th>Carbon content of fuel (kg per MMBTU)</th>
<th>Carbon emissions (t per MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal</td>
<td>Advanced pulverized coal generation</td>
<td>650</td>
<td>8.8</td>
<td>3.246</td>
<td>0.038</td>
<td>4.5</td>
<td>17.4</td>
<td>94</td>
<td>0.823</td>
</tr>
<tr>
<td></td>
<td>Advanced pulverized coal generation with carbon capture and sequestration</td>
<td>650</td>
<td>12.0</td>
<td>5.2</td>
<td>0.081</td>
<td>9.5</td>
<td>23.8</td>
<td>9.4</td>
<td>0.112</td>
</tr>
<tr>
<td></td>
<td>Integrated gasification combined cycle</td>
<td>600</td>
<td>8.7</td>
<td>4.4</td>
<td>0.062</td>
<td>7.2</td>
<td>17.2</td>
<td>94</td>
<td>0.814</td>
</tr>
<tr>
<td></td>
<td>Integrated gasification combined cycle with carbon capture and sequestration</td>
<td>520</td>
<td>10.7</td>
<td>6.6</td>
<td>0.073</td>
<td>8.5</td>
<td>21.2</td>
<td>9</td>
<td>0.100</td>
</tr>
<tr>
<td>Natural gas</td>
<td>Conventional combined cycle</td>
<td>620</td>
<td>7.05</td>
<td>0.9</td>
<td>0.013</td>
<td>3.6</td>
<td>28.2</td>
<td>53</td>
<td>0.374</td>
</tr>
<tr>
<td></td>
<td>Advanced combined cycle</td>
<td>400</td>
<td>6.43</td>
<td>1.0</td>
<td>0.015</td>
<td>3.3</td>
<td>25.7</td>
<td>53</td>
<td>0.342</td>
</tr>
<tr>
<td></td>
<td>Advanced combined cycle with carbon capture and sequestration</td>
<td>340</td>
<td>7.525</td>
<td>2.1</td>
<td>0.032</td>
<td>6.8</td>
<td>30.1</td>
<td>5</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Conventional combustion turbine</td>
<td>85</td>
<td>10.85</td>
<td>1.0</td>
<td>0.007</td>
<td>15.5</td>
<td>43.4</td>
<td>53</td>
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<td></td>
<td>Advanced combustion turbine</td>
<td>210</td>
<td>9.75</td>
<td>0.7</td>
<td>0.007</td>
<td>10.4</td>
<td>39.0</td>
<td>53</td>
<td>0.518</td>
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<td></td>
<td>Fuel cells</td>
<td>10</td>
<td>9.5</td>
<td>7.1</td>
<td>0.000</td>
<td>43.0</td>
<td>38.0</td>
<td>59</td>
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<td>Uranium</td>
<td>Advanced nuclear</td>
<td>2,204</td>
<td>10.40</td>
<td>5.5</td>
<td>0.093</td>
<td>2.1</td>
<td>2.0</td>
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<td>Wind</td>
<td>Onshore wind</td>
<td>100</td>
<td>–</td>
<td>2.2</td>
<td>0.046</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td></td>
<td>Offshore wind</td>
<td>400</td>
<td>–</td>
<td>6.2</td>
<td>0.074</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td>Solar</td>
<td>Solar thermal</td>
<td>100</td>
<td>–</td>
<td>5.1</td>
<td>0.067</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<tr>
<td></td>
<td>Solar photovoltaic</td>
<td>150</td>
<td>–</td>
<td>3.9</td>
<td>0.025</td>
<td>–</td>
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<td>Hydroelectric</td>
<td>Conventional hydroelectric</td>
<td>500</td>
<td>–</td>
<td>2.9</td>
<td>0.014</td>
<td>–</td>
<td>–</td>
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<td></td>
<td>Pumped storage</td>
<td>250</td>
<td>–</td>
<td>5.3</td>
<td>0.018</td>
<td>–</td>
<td>–</td>
<td>–</td>
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<td>Biomass</td>
<td>Biomass combined cycle</td>
<td>20</td>
<td>12.35</td>
<td>8.2</td>
<td>0.356</td>
<td>17.5</td>
<td>–</td>
<td>89</td>
<td>1.093</td>
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<td>Biomass bubbling fluidized bed</td>
<td>50</td>
<td>13.5</td>
<td>4.1</td>
<td>0.106</td>
<td>5.3</td>
<td>–</td>
<td>89</td>
<td>1.195</td>
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<td>Geothermal</td>
<td>Geothermal dual flash</td>
<td>50</td>
<td>–</td>
<td>6.2</td>
<td>0.132</td>
<td>–</td>
<td>–</td>
<td>54</td>
<td>0.054</td>
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<td></td>
<td>Geothermal binary</td>
<td>50</td>
<td>–</td>
<td>4.4</td>
<td>0.100</td>
<td>–</td>
<td>–</td>
<td>54</td>
<td>0.054</td>
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<tr>
<td>Municipal solid waste</td>
<td>Municipal solid waste</td>
<td>50</td>
<td>18</td>
<td>8.3</td>
<td>0.383</td>
<td>8.8</td>
<td>–</td>
<td>91</td>
<td>1.634</td>
</tr>
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</table>

Table A.1: EIA list of power plant technologies
Appendix B

Alphabetic list of variables

\( \mathbf{A}_t^{\text{cost}} \): LP matrix of \( lp_t^{\text{cost}} \)
\( \bar{A}_t^{\text{cost}} \): upper LP matrix of \( lp_t^{\text{cost}} \)
\( \underline{A}_t^{\text{cost}} \): lower LP matrix of \( lp_t^{\text{cost}} \)
\( \mathbf{A}_t^{\text{em}} \): LP matrix of \( lp_t^{\text{em}} \)
\( \bar{A}_t^{\text{em}} \): upper LP matrix of \( lp_t^{\text{em}} \)
\( \underline{A}_t^{\text{em}} \): lower LP matrix of \( lp_t^{\text{em}} \)

\( B_k \): build history until time \( t_{k-1} \)
\( \bar{b}_k \): build decision at time \( t_k \)
\( \bar{b}_{k,\text{tec}} \): build decision in technology \( \text{tec} \) at time \( t_k \)
\( b_t^{\text{cost}} \): LP constraint of \( lp_t^{\text{cost}} \)
\( b_t^{\text{em}} \): LP constraint of \( lp_t^{\text{em}} \)

\( bu_k(t) \): intra-period capacity build-up up to year \( t \)
\( \bar{c}_k \): pre-decision capacity at time \( t_k \)
\( c_{k,\text{tec}} \): pre-decision capacity in technology \( \text{tec} \) at time \( t_k \)

\( \text{capacity}_{\text{tec}} \): nominal capacity (in MW) of a plant of technology \( \text{tec} \)
\( c_t^{\gamma} \): available capacity during year \( t \)
\( c_{t,\text{tec}}^{\gamma} \): available capacity of technology \( \text{tec} \) during year \( t \)

\( CC \): matrix of capital costs
\( \bar{c}_t \): vector of capital costs at the end of year \( t \)
$c_{cost, tec}$: capital cost for tech $tec$ at the end of year $t$
$c_{overnight}$: overnight capital cost of a plant of technology $tec$

$\bar{d}_t$: base demand vector
$\tilde{d}_t$: demand vector for year $t$
$d_{t,h}$: demand in hour $h$ of year $t$

$d_t^{\text{peak}}$: peak demand during year $t$
$d_t^{\text{peak}}$: peak demand during period $k$

$D^P$: average demand matrix for partition $P$
$d_t^P$: average demand vector for year $t$ and partition $P$
$d_t^{P,l}$: average demand during load block $l$ of year $t$
$\bar{d}_{dec}$: decay of legacy portfolio
$dec_k$: decay of legacy portfolio during period $k$
$df(\cdot)$: discount factor

$\bar{d}_{dp_t}$: dispatch decision for year $t$
$ds_k$: dispatch strategy at time $t_k$ for period $k + 1$
$\bar{e}_c$: vector of (temporary) emissions caps
$\bar{em}_k$: (temporary) emissions cap at the end of year $t$

$em_k(\cdot)$: emissions generated during period $k$
$em_t$: total carbon emissions in year $t$

$em_{tec}^H$: carbon emissions per plant of technology $tec$ and hour of operation

$es_k$: emissions stock at time $t_k$
$f_k(\cdot)$: transition function
$f_t^{\text{cost}}$: objective function of $l p_t^{\text{cost}}$
$f_t^{\text{em}}$: objective function of $l p_t^{\text{em}}$

$\bar{f}_c$: vector of annual fixed O&M cost
$f_{c, tec}$: annual fixed O&M cost of technology $tec$
$g(\cdot)$: total cost function

$g_k$: total cost function (period $k$)
$g_k^{CC}$: capital cost function (period $k$)
$g_k^{EP}$: emissions penalty function (period $k$)
$g_k^F$: fixed O&M cost function (period $k$)
$g_k^V$: variable O&M cost function (period k)
$gp^k$: vector of gas prices
$gp_k$: vector of gas prices in period k
$gp_t$: gas price at the end of year t

growth: demand growth vector

growth_t: demand growth during year t

$h_{t,l,i}$: hour i of load block l of year t
$HC_k$: historical cost of build until time $t_{k-1}$
$hc_k$: historical cost of build at time $t_k$

heatrate_{tec}: heatrate of technology tec

$h_{tc}^{cc}$: upper bound for random walk of capital cost of technology tec
$h_{tc}^{ec}$: upper bound for random walk of emissions cap
$h_{tc}^{gp}$: upper bound for random walk of gas price

$ib_{k,tec}$: installed base of technology tec at time $t_k$

$\tilde{L}_t$: legacy portfolio at time $t_0$
$le_{tec}$: legacy assets of technology tec at time $t_0$

lifetim_{tec}: expected lifetime of a plant of technology tec

$lo_{tc}^{cc}$: lower bound for random walk of capital cost of technology tec
$lo_{tc}^{ec}$: lower bound for random walk of emissions cap
$lo_{tc}^{gp}$: lower bound for random walk of gas price

$lp_t^{cost}$: LP for dispatch year t, lowest cost, emissions constraint
$lp_t^{em}$: LP for dispatch year t, lowest emissions, cost constraint

$\mu_{tc}^{cc}$: mean value for random walk of capital cost of technology tec
$\mu_{tc}^{ec}$: mean value for random walk of emissions cap
$\mu_{tc}^{gp}$: mean value for random walk of gas price

$n^P$: number of periods
$n^P$: size of partition / number of load blocks

$n^{peak}$: number of hours of peak load block

$n^T$: number of technologies

$n^Y$: number of years (all periods)

$O$: output matrix for base year

$\tilde{O}_k$: output vector for tech k and base year
\( o_{tec,h} \) : output of a plant of technology \( tec \) during hour \( h \) of the base year

\( O^P_{tec} \) : output matrix for technology \( tec \) and partition \( P \)

\( \bar{o}^P_{tec,t} \) : output vector for technology \( tec \), year \( t \) and partition \( P \)

\( o^P_{tec,t,l} \) : avg. output of a plant of technology \( tec \) during load block \( l \) of year \( t \)

\( \Omega \) : vector of noise vectors

\( \bar{v}_k \) : noise vector at time \( t_k \)

\( P \) : partition matrix

\( \bar{P}^t \) : partition of year \( t \)

\( P_{t,l} \) : load block \( l \) of year \( t \)

\( p(t) \) : number of period that includes year \( t \)

\( ppt \) : penalty per excess ton of CO\(_2\)

\( r \) : discount rate

\( rcd \) : ratio of capacity to demand (target)

\( \sigma_{tec}^{cc} \) : std. dev. for random walk of capital cost of technology \( tec \)

\( \sigma^{ec} \) : std. dev. for random walk of emissions cap

\( \sigma^{gp} \) : std. dev. for random walk of gas price

\( \tilde{t} \) : decision times and end of last period

\( t_{\text{stop}}^{cc} \) : stop time for random walk of emissions cap

\( U_{t,tec}() \) : technological learning at the end of year \( t \) for technology \( tec \)

\( l_{tec} \) : technological learning factor for technology \( tec \)

\( \bar{u}_k \) : control at time \( t_k \)

\( u_{lb}^{cst} \) : upper bound of \( l_{lb}^{cst} \)

\( u_{he}^{em} \) : upper bound of \( l_{he}^{em} \)

\( v_{ct} \) : total variable O&M cost in year \( t \)

\( v_{c}^{h,tec} \) : variable O&M cost per plant of technology \( tec \) and hour

\( v_{c}^{H,fuel} \) : fuel cost per plant of technology \( tec \) and hour of operation

\( v_{c}^{H,other} \) : other variable O&M cost per plant of technology \( tec \) and hour

\( x \) : vector of state vectors

\( \bar{x}_k \) : state vector at time \( t_k \)
Bibliography


