Optimal Investment in Wind and Solar Power in California

by

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Fall 2008
The dissertation of Matthias Fripp is approved:

Chair ________________________________ Date ____________

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Abstract
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Wind and solar electricity are increasingly attractive as their costs decline and greater value is given to avoiding greenhouse gas emissions. However, these technologies generate power only when the wind and sun are available, so it is unclear how large a role they should play in the future power system.

To address this question, I developed a new model that identifies the least expensive set of investments in wind, solar and conventional generators and transmission lines to provide a reliable power supply for California in 2014–25, while accounting for the value of avoiding carbon dioxide emissions. The Switch model (a loose acronym for Solar, Wind, Hydro, and Conventional generators and Transmission) simultaneously optimizes long-term investments in generators and transmission capacity and hourly plans for how to operate this equipment. Weather conditions during each simulated hour are based on historical conditions, so that the optimization incorporates any correlation between wind, sunshine and loads.

This model shows how the optimal design of the power system changes depending on one’s assumptions about the value of reducing greenhouse gas emissions and
the direct costs of generators and fuels. Conversely, it can also show the minimum cost of achieving any level of emission reductions.

I use the Switch model to develop a “supply curve” for emission reductions from the electric power system, which could help policymakers allocate emission reductions efficiently among all sectors of the economy. I also investigate the economic factors that are likely to limit the use of renewable power. I find that there is no sharp limit to the use of these technologies, even when providing half or more of the system’s power. However, the cost of power could rise gradually as these technologies are used on a larger scale: in part because they will need increasing proportions of backup power from other sources, but more importantly, because they will eventually begin to generate unneeded power during some hours. I conclude with a quick look at the potentially strong synergies between a highly renewable power system and plug-in hybrid-electric vehicles, which could make effective use of otherwise-surplus power.
I dedicate this dissertation to my family, both new and old, present and absent. To my grandmother who helped support me through college, to my parents who taught me the value of caring and questioning, and most of all, to Kamal, whose love and enthusiasm made this work seem easy.
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Part I: The Switch Model

CHAPTER 1: INTRODUCTION

The electricity sector contributes about 21 percent of global greenhouse gas emissions, and about 22 percent of California’s emissions (Bemis 2006; Rohde 2006). In recent years, awareness has grown of the need to reduce these emissions, and California has begun to adopt policies to promote the use of renewable electricity or otherwise restrict greenhouse gas emissions from this sector. Two policies are particularly noteworthy: the state’s renewable portfolio standard (RPS), and the California Global Warming Solutions Act of 2006, more commonly known as Assembly Bill 32 (AB32). The RPS requires that California utilities supply 20 percent of the state’s electricity from renewable sources by 2020, a target that may grow to 33 percent by 2030. AB32 requires the state to roll back greenhouse gas emissions to 1990 levels by 2020. It remains unclear whether the electricity sector will be given a stricter or looser emissions target than the state as a whole, or how the electricity-sector requirements under AB32 will be integrated with those of the RPS.

These are useful steps to reduce the social and environmental harm caused by greenhouse gas emissions. However, given the importance of the issue, strikingly little attention appears to have been given to the question of what is the “right” target for reducing greenhouse gas emission reductions from the electricity sector. Instead, goals appear to have been set based on political expediency and technical feasibility, rather than any analysis of whether they are the “right” target for California.

Environmental economics suggests that the “right” target for the electricity sector (or, indeed for the whole economy), would be the level at which the dollar value of the damage done by releasing an extra ton of carbon dioxide is equal to the marginal cost
of reducing emissions by one more ton; if releasing another ton of carbon dioxide will do $50 worth of damage, then we should be willing to pay up to $50 per ton to avoid doing so.\footnote{This argument is an oversimplification if damage is done outside of California; however, it does hold if the state considers damage everywhere equivalent to damage in California, or if the state envisions a cooperative, global effort, where each jurisdiction does “its share” to reduce greenhouse gas emissions.} Estimating the damage caused by each ton of carbon dioxide emissions is a daunting task, and it may be easier in the near future for the state to continue using somewhat arbitrary statewide targets along the lines of AB32, possibly with different targets for each sector of the economy. However, even in this case, the most efficient allocation of targets among sectors would be the one that ensures that marginal costs of emission reductions are the same in every sector.

To set such economically efficient emission targets, planners would need to know the marginal cost of greenhouse gas emission reductions corresponding to various levels of emission reductions from the electricity sector. Unfortunately, little attention has been given to this question.

This paper introduces a new model which can be used to fill this void. The model is called “Switch,” a loose acronym for “Integrated Solar, Wind, Conventional and Hydroelectric Generation and Transmission Planning Model.” It provides an analytical bridge between the marginal cost of carbon dioxide emissions and the composition of the electric power system. Based on forecasts of the future costs for fuel, new equipment and carbon dioxide emissions, the Switch model identifies the lowest-cost set of investments in wind, solar and natural gas generators and transmission lines in California over the next 20 years. For any assumption about the cost of greenhouse gas emissions, the Switch model reveals the optimal composition of the power system over the next 20 years. For example, if a cost of $50 per ton is assigned to carbon dioxide emissions, it is
then possible to see what would be the optimal share of renewable energy in the power system (i.e., the optimal RPS target), avoiding any greenhouse gas emissions that can be prevented at a lower cost. Alternatively, the model can be run repeatedly with different carbon dioxide costs, to develop a “supply curve” showing how many tons of greenhouse gas emissions can be eliminated from the electricity sector, at a marginal cost below each tax level. This supply curve can then be compared to those from other sectors to develop a harmonized set of targets for each sector, achieving a statewide target such as that in AB32, at the lowest possible cost.
CHAPTER 2: PREVIOUS WORK

California has invested substantial resources in studying the economic and technical performance of the power system, in future scenarios with higher levels of renewable energy.

The state’s flagship power system planning process is the work done for the California Energy Commission’s biennial Integrated Energy Policy Reports (IEPR). For the 2007 IEPR, analysts considered a number of scenarios, combining increased investments in renewable energy and efficiency, either in California alone or throughout the interconnected region overseen by the Western Electricity Coordinating Council (WECC) (CEC 2007a; Jaske 2007). Unfortunately, this study explicitly forewent any assessment of the change in costs of equipment over time, and considered only specific combinations of wind, solar, natural gas and other resources, rather than seeking an optimal combination of technologies. Similar approaches have been taken by individual electric utilities, as part of their long-term procurement planning (Idaho Power 2006; PacifiCorp 2007; Ringer 2007; Wiser and Bolinger 2006; Woodward 2007). The cost of renewable power equipment has historically declined rapidly, and may continue to do so in the future. It is likely that a study using projected costs, and choosing an optimal combination of technologies, would yield lower costs than the portfolios considered in the IEPR or other integrated resource plans. Consequently, this study does not give a clear picture of the cost of emission reductions under an optimally designed policy.

In 2006, the California Energy Commission commissioned the Intermittency Analysis Project (IAP) (Porter and IAP Team 2007a, 2007b), a detailed technical analysis of several scenarios working toward a 33 percent RPS in California by 2020. Project participants used heuristic rules and a detailed model of the state’s transmission system to
choose a mix of renewable resources, conventional generators and transmission line upgrades that would reliably serve increasing electricity loads, while incorporating up to 25 percent renewable energy. The operation of this hypothetical system was then simulated, using three years of hourly data on electricity loads, potential wind power production, and potential solar power production. This is the first grid-scale study to base its analysis on simultaneous, historical hourly electricity loads, wind, solar and hydroelectric conditions; this ensures that its results reflect any correlation that may exist between these. Conditions were also modeled on a geographically specific basis, so that relations between different regions could be reflected in the model results. Overall, the authors found that the addition of these renewable resources would add about 10 percent to the state’s need for flexible generation resources, on time scales from minutes to days.

The IAP broke new ground in assessing the behavior of the power system with high levels of renewable power. However, it largely ignored economic factors, so it is difficult to judge the cost of the IAP’s future power system, or whether costs could be reduced by using more or less renewable power, or by changing the mix among different renewable resources. The IAP indicates that by 2020 California could use one particular renewable energy portfolio with little technical upheaval; however, it does not help reveal how much renewable power the state should ultimately seek to use.

The IEPR and IAP scenario studies give valuable information about the economic costs and technical feasibility of certain, specific responses to California’s greenhouse gas policies. However, they do not provide much information that can be used to develop the best policies in the first place.

Three other studies (none in California) have sought to identify optimal combinations of renewable and conventional resources on a large scale; their methods could be
used to help identify the best policy for California, rather than simply assess the implications of a particular policy.

Each of these three optimization studies starts with forecasts of future costs of wind and natural gas generators and fuels, and time-varying power production at potential wind farm sites. They divide a large study region into several zones, and then optimize power system investments in each zone during one or more investment periods. Between investment periods, they also optimize the use of equipment during a number of hourly dispatch periods. Some studies also assess how the investment and dispatch decisions change when costs are assigned to carbon dioxide emissions.

Short et al. (2003) divide the United States into 356 wind regions, and optimize the installation of wind farms and conventional generators over 25 two-year investment periods, from 2000 through 2050. Their model also chooses optimal operational strategies for four dispatch periods within each investment period, corresponding to the average wind conditions during each season of the year, and maintains planning and operational reserve margins to ensure system reliability. Transmission between load zones uses a “postage-stamp” approach, with a fixed price per MWh and no details about the transmission network. This model has a remarkable amount of spatial detail, but only a weak representation of the temporal variation of wind speeds. To overcome this limitation, the model uses formulas that estimate the reliable capacity of wind sites, based on their average capacity factors and the distance between them; this approach extends the treatment of wind power in traditional long-term integration plans, to reflect the smoothing of the power supply when multiple wind sites are aggregated. This model neglects the effect of carbon dioxide emission costs.
DeCarolis and Keith (2006) develop an optimization model with lower spatial resolution and higher temporal resolution than Short et al. (2003). Their model considers potential wind farms at 5 locations in Montana, Wyoming, Texas, North Dakota, Iowa and Illinois; a radial transmission network linking these locations; simple and combined cycle gas turbines in Illinois; and a compressed air energy system in Iowa, all serving electricity loads in Chicago, Illinois. This model optimizes installation and dispatch of this equipment for one investment period in 2020, based on 5 years of hourly wind and load data. Sensitivity analyses are performed for a wide range of carbon dioxide and fuel costs. However, this model neglects the evolution of the power system over time and considers loads only in one part of the study region. These limitations may be insurmountable, given the complexity of the dispatch component of this model (which considers over 40,000 hours of wind and load data).

Neuhoff et al. (2008) optimize investments and dispatch choices for new and existing natural gas and wind generators, and existing hydroelectric plants, during four 5-year investment periods, each containing 1040 dispatch periods. Their model divides the UK into 7 regions, joined by a radial transmission network. The 1040 dispatch periods are created by binning the hourly system-wide electricity loads for each week of 1995 into 20 discrete levels. The potential wind power production in each region during each dispatch period is found by averaging potential production at all meteorological stations within that region, during the corresponding historical hours. Electricity loads in each region during each hour are calculated as a fixed percentage of the nationwide electric load during that hour. This model incorporates an exogenous carbon permit price, but the authors do not perform any sensitivity studies with this parameter. Although this model uses an optimization framework, the authors raise their forecast of the price of
wind power plants, to ensure that they supply exactly 40 percent of the system’s electricity, and no more. This allows them to study the other power system investments that would be needed to accommodate this much wind power, but prevents them from assessing whether this is the optimal amount of wind power to use.

The Switch model is in the same family as these three models, but focuses on California. It combines some strengths of these three models, but also adds some capabilities that are absent from all of them:

- It considers solar resources in addition to wind power, a feature missing from all previous optimization studies. As will be discussed below, the wind and solar power are available at highly complementary times in California; they may be complementary elsewhere as well.
- Unlike previous optimization models, the Switch model uses load forecasts for each dispatch period, that are based on conditions in each location during particular historical hours. This ensures that investment choices reflect any correlations that may exist between regional loads and/or renewable resources anywhere in the state.
- Like DeCarolis and Keith (2006), the Switch model chooses optimal investments in transmission lines, in addition to generators.
- Like Short et al. (2003), the Switch model uses reliability criteria and economic assessments that consider the risk of forced outages of equipment.
- The Switch model uses wind data that are calculated specifically for likely wind turbine locations and hub heights, better reflecting any correlation that may exist with electricity loads. In contrast, DeCarolis and Keith and Neuhoff et al. use hourly weather station data with simple scaling rules; this may yield different
timing than would be found at wind farm sites and heights. Short et al. use average wind speeds for individual seasons, which provide insufficient detail to assess finer-scale correlation.

- The Switch model uses a linear “transport” model for operation of the electricity transmission system. For practical purposes, this is similar to the approach taken by DeCarolis and Keith and Neuhoff et al.; both of these studies use a radial transmission network that can transmit power as needed down each transmission link.\(^2\) As will be discussed below, this neglects the possibility that some current scheduled for one transmission path may instead follow another path, overloading the system.

Optimization models are able to sift through a tremendously wide range of potential future configurations of the electric power system. However, in order to find solutions in a reasonable period of time on existing computers, they must generally use a linearized representation of the transmission network (as just mentioned) and limited spatial and temporal resolution. The Switch model uses a spatial and temporal resolution that falls somewhere between the other optimization models I have just discussed (Table 1). Its greatest weakness may be in the number of dispatch periods considered; in order to overcome this, I anticipate using a bootstrap approach with multiple model runs, to ensure that results are robust, regardless of which dates are sampled (Neuhoff et al. use a similar approach).

\(^2\) Neuhoff et al. actually use a linearized DC representation of the existing power network, which would give a good estimate of the flow of current through alternative paths, if their model had any parallel paths. However, this model cannot be extended to allow for endogenous expansion of the transmission network.
Table 1. Resolution and capabilities of Switch and other power system investment optimization models

<table>
<thead>
<tr>
<th></th>
<th>Switch</th>
<th>Short et al.</th>
<th>DeCarolis and Keith</th>
<th>Neuhoff et al.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of zones for load or fossil generators</td>
<td>19</td>
<td>134</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Number of wind sites</td>
<td>229</td>
<td>356</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Number of solar sites and orientations</td>
<td>464</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Number of investment periods</td>
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<td>25</td>
<td>1</td>
<td>4</td>
</tr>
<tr>
<td>Number of dispatch periods per investment period</td>
<td>288</td>
<td>4</td>
<td>43800</td>
<td>1040</td>
</tr>
<tr>
<td>Endogenous transmission expansion</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Includes existing infrastructure</td>
<td>yes</td>
<td>yes</td>
<td>no</td>
<td>yes</td>
</tr>
</tbody>
</table>
CHAPTER 3: MODEL DESIGN

This chapter provides more details on the design of the Switch model. Then
Chapter 4 discusses the specific data that have been used to run the model for the Cali-
fornia power system over the period of 2010–25. Finally, later chapters show the result of
these model runs.

The Switch model is a continuous, linear optimization model, which incorporates
data on existing power plants and transmission lines, as well as spatially and temporally
varying wind, solar and hydroelectric resources, and electricity loads, over a large geo-
graphic area. This model identifies the lowest-cost combination of annual investments
and hourly operational decisions, to satisfy expected electricity loads over a 16-year pe-
riod, while accounting for the environmental cost of carbon dioxide emissions.

Specifically, the model’s objective is to minimize the present value of the cost of
power plants, transmission lines, fuel and carbon dioxide emissions in California over the
next 16 years.

It has two major sets of decision variables: every four years, it decides how much
to build of several different types of power plant (wind, solar, natural gas) in each of 18
geographic zones, and how much transmission capacity to build between these zones. It
also chooses whether to keep existing baseload plants in operation during each of these
four-year periods, and how much The second set of decisions are made for every hour of
several representative days within each of these four-year periods. For each hour, the
model chooses the amount of power to generate from each new or existing dispatchable
power plant, the amount of energy to store at each pumped-hydroelectric facility, and
the amount of power to transfer along each transmission corridor.
These decisions are constrained by a requirement that forecast electricity loads must be satisfied every hour, and a reserve margin of 15 percent must be maintained in every hour. Additional constraints ensure that hydroelectric facilities are operated in accordance with their historical limits and that power plants are retired at the end of their expected life.

More details on the formulation of the model are given in the following sections.

3.1 Simulation Calendar

The Switch model makes investment and operation choices for several future, multi-year “investment periods.” Each investment period includes a number of dispatch periods of one hour each. The model makes investment decisions at the start of each investment period, and then chooses how to dispatch generators and transmission lines to satisfy electricity loads during each dispatch hour. Throughout this paper, the term “investment period” refers to the multi-year investment period, while the terms “operational,” “dispatch” or “hourly” refer to decisions and constraints that apply to the individual dispatch periods within each investment period.

Due to computational constraints, the Switch model can only incorporate a limited number of hours during each investment period; for most of the work reported here, each investment period includes 24 dates, represented by 24 hours each. For the sensitivity studies reported later in this thesis, the sampling rate has been reduced to 12 sampled dates during each investment period, represented by 12 hours each.

Electricity loads vary over time, as do the availability of hydroelectric, wind and solar power, and all of these variations are due in large part to variations in the weather. To account for any correlation between loads and the availability of renewable resources, each date in the Switch model is matched to a single historical date. Then, loads, wind,
solar and hydroelectric availability throughout the state during that simulated date are derived from the conditions that occurred during the matching historical date.³

Conditions other than the weather are assumed to be identical for all dispatch periods within each investment period. These include such factors as average load growth, equipment cost projections, fuel price forecasts or plant retirements: any generator that is operational at the beginning of each period is assumed to be usable for all hours in the period, and forecasts of loads and prices for the first year of the period are assumed to apply to all hours during the period. Expenditures for fuel or carbon taxes during each period are also treated as if they occurred during the first year of the period.

Because the Switch model considers a limited number of hours, there is some risk that it will make different investment choices, depending on which historical dates are chosen for study. However, in my experience, the model has made generally consistent investment choices, regardless of which dates are sampled.

As will be discussed in section 3.10.1, the Switch model does not consider variations in load and renewable resources on a shorter than hourly timescale. These variations in are important, but little data is available on them, and representing them directly would make the model unsolvable on current computers. Instead, I have focused my effort on understanding the role that renewable energy can play in satisfying the power system’s needs for reliable power on an hourly and greater time scale (i.e., capacity and energy).

³ This arrangement allows for some diversity in the dates selected, but also retains a chronological relationship between individual hours of the day. A chronological relationship is necessary in order to model daily hydroelectric energy constraints; it also allows for the possibility of ramp rate constraints for thermal generators (not included in the current version of the model).
3.2 Geographic Extent

The Switch model divides the study region into several “load zones.” High-voltage transmission lines can join the centers of any two zones. All central-station generators (e.g., combined-cycle natural gas plants, solar-thermal electric plants, or wind farms) are treated as if they were concentrated at the center of their load zone, so that they can deliver power directly to the large-scale transmission network. Within each load zone, the local transmission and distribution network is represented by a single value for “local transmission and distribution capacity,” which indicates the maximum zone-wide load that can be served by central-station generation technologies or power imports. During each investment period, the model chooses whether to build or expand transmission capacity between zones or within each zone.

3.3 Forced Outage Risks

Power plants and transmission lines can stop working correctly at any time, due to mechanical failure, damage by weather, or other factors. This risk is often characterized by assigning a “forced outage rate” to each plant or transmission line. In the Switch model, this rate refers only to non-weather related risks; risks associated with wind, solar and hydro conditions are handled directly by sampling from historical conditions.

If many plants or transmission lines have forced outages at the same time, parts of the power system can suffer blackouts. In generation adequacy studies, it is common to address this risk by running a Monte Carlo simulation of the power system over many possible future hours. During each hour, each piece of equipment is randomly placed in or out of service according to its forced outage rate. If there are many hours when loads cannot be served due to equipment failures, then more generation or transmission capacity is added to the simulated power system, and the process is repeated until the system is
reliable enough. These simulations can also reveal the typical costs of operating the system under the range of possible future conditions.

This approach is too computationally intensive to implement within an optimization model, so the Switch model addresses risk in three other ways.

First, rather than consider all possible permutations of forced outages, the Switch model requires that enough power plants and transmission lines be built to provide a reserve margin of generating capacity at all locations in all hours. California law requires that each energy supplier maintain a planning reserve margin of 15 percent in all hours; that is, if they suffered no forced outages, they would be able to supply up to 15 percent more power than their expected future loads in each hour. The 2007 IEPR scenario analyses also adopted this as their reliability target (CEC 2007a; Jaske 2007). For simplicity, and to maintain consistency with these procurement policies, the Switch model does the same. This margin is substantially more than the forced outage rate of power plants, and generally appears to provide adequate reliability (Woodward 2007).4

Second, the Switch model performs all economic analysis on an expected-value basis. It would be unrealistic to expect to obtain 100 percent of the rated power from a plant at all times. Instead, for its economic analysis, the Switch model de-rates the nameplate capacity of every power plant and transmission line based on its forced outage rate. For example, if a natural gas power plant has a nameplate capacity of 100 MW and a forced outage rate of 5 percent, then the Switch model only assumes that it can obtain 95 MW from that plant on average in all future hours. This ensures that the costs calcu-

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4 In practice, the Switch model usually creates the reserve margin by adding natural gas generation capacity that is not expected to be used often; since they have relatively low capital costs, these generators add little to the cost of the power system. In a more detailed treatment, this reserve capacity might be increased or decreased somewhat, again with little effect on the average cost of power. Consequently, the investment strategy suggested by Switch is likely to be very similar in cost and makeup to the plan that would be obtained by considering outage risks in much greater detail.
lated for operation of the power system are based on the resources that are expected to be available in each hour, not the maximum that could be available if every piece of equipment worked correctly.\(^5\) This de-rated capacity is similar to the “unforced capacity” used for generating plants in the NYISO and PJM capacity auctions (FERC 2007).

Third, the Switch model respects constraints on existing transmission lines that have been established as part of the WECC’s path rating process. These constraints are lower than the thermal limits of individual lines, and reflect power system engineers’ best estimates of the amount of power that can be carried reliably along each path, without risking instability if any line or generator fails.

The Switch model implements the first two approaches to risk by making two sets of operating decisions simultaneously. The first set of decisions shows how the system would be operated if all equipment worked correctly, but each load zone needed 15 percent extra electricity in each hour. The second set of decisions describes how the system is actually expected to be operated (on average), satisfying loads in every hour, but only using as much capacity from each generator or transmission line as is expected to be available. This dual approach only applies to operational decisions. The model creates only one investment plan, and that plan must provide enough capacity to meet both sets of operational constraints. Consequently, the Switch model makes investment decisions that satisfy the planning reserve margin requirement, but are also expected to yield the lowest possible combination of capital and operating costs.

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\(^5\) This discussion neglects the scheduled outage rate, for required maintenance that can be scheduled as needed throughout the year. For non-baseload plants, it is assumed that maintenance can be scheduled for times when the plant is not needed, so it will not affect the economic calculations. For baseload plants, the expected output in each hour is de-rated by both the forced outage rate and the scheduled outage rate.
3.4 Investment and Dispatch Choices

The primary information provided by the Switch model is a set of choices about power system investments and operational choices that are expected to yield a reliable supply of power at the lowest possible cost.

Four sets of choices constitute a long-term power-system investment plan, which is the most important output from the Switch model. These choices are made at the beginning of each investment period:

1. How much power generation capacity of various types (wind, solar or natural gas) to add in each load zone.
2. How much transmission capacity to add between each pair of load zones.
3. How much local transmission and distribution capacity to add within each load zone.
4. Whether or not to run each baseload power plant (coal, nuclear, cogeneration) during each investment period (i.e., a choice is made once each period, and the plant produces the same amount of power in all hours of the period).\(^6\)

The remaining choices show the optimal use of this infrastructure, and can be used to calculate how much power is expected to come from renewable or conventional sources over the course of the simulation. These choices are made for each hour during each study period. As discussed above, each of these sets of choices is made twice simultaneously: once on a reserve-planning basis, and again on an expected-value basis:

1. How much power to generate from dispatchable generators (natural gas or hydroelectric), in each load zone. (Hourly dispatch decisions are not needed for baseload generators or intermittent renewables. Baseload plants produce the same

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\(^6\) In principle, baseload plants could be mothballed for one study period and then operated in a later period, but this appears unlikely, since the economic forces that drive them into disuse persist in later periods.
amount of power during all hours. Wind and solar facilities produce an amount of power equal to an exogenously specified hourly capacity factor, multiplied by the capacity of the facility built by the model. These hourly capacity factors are calculated based on the wind or sunlight at each location on the corresponding historical date.)

2. How much power to store at each pumped-hydroelectric storage facility.

3. How much power to transfer along each transmission corridor.

It should be noted that the Switch optimizer treats the electricity transmission system like a transportation network, in which the system operator can decide exactly how much power to send through each corridor in each hour. This approximation makes the optimization problem linear and solvable in a reasonable period of time, but it neglects some constraints on the operation of the real, physical network. This issue is discussed in more detail below, under “Treatment of Transmission Lines.”

3.5 Economic Evaluation

The total cost of delivering power over the full study period includes five components: (1) the capital cost of building power plants, (2) operations and maintenance (O&M) costs incurred each year at active power plants, (3) variable O&M costs incurred for each megawatt-hour of power produced each plant, (4) the cost of any fuel used to generate electricity, and (5) a “carbon cost” that reflects the direct or indirect cost of each metric ton of carbon dioxide emitted by a power plant.7

For transmission lines, only a capital cost and annual fixed O&M cost are considered. The cost of building and maintaining local transmission and distribution infrastruc-

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7 The “carbon cost” may be a proposed tax, or may be a marginal benefit or cost of emission reduction that is used only for analytical purposes. This issue is discussed further under “Carbon Dioxide Emission Taxes,” below.
ture is represented by a simple annual payment that must be made to finance and main-
tain each MW of capacity in each zone.

Capital costs are amortized as an annual payment over the expected life of each plant or transmission line, and only those payments that occur during the study are con-
sidered. This approach avoids billing the full cost of facilities, if they continue to yield benefits after the study finishes. For optimization purposes, all costs during the study are discounted to a present-day value using a common discount rate, so that costs incurred later in the study have less impact than those incurred earlier. All costs are specified in real terms, indexed to a current reference year (e.g., 2007).

3.6 Constraints

As discussed in section 3.3, the Switch model includes two sets of constraints. The first set requires that the power system maintain a planning reserve margin: it must be able to provide up to 15 percent extra power in every load zone in every hour, if all generators and transmission lines are working correctly. The second set ensures that the model develops an operational plan that provides the lowest-cost power, on an expected-
value basis, based on the generation and transmission capacity that is expected to be available, on average, in each hour of the study.

These are the constraints which the Switch model respects:

General constraints:

1. Baseload generating capacity in each load zone during each investment period can only be activated if it exists. (i.e., the operating baseload capacity must be less
than or equal to the amount that existed at the start of the study, plus any additions, less any retirements).

2. The local (intra-zone) transmission and distribution capacity in each zone must equal or exceed the electricity demand in that zone for all hours, after subtracting the output from distributed photovoltaic systems.

**Reserve margin planning** (these constraints apply to the reserve margin version of the operational decisions):

3. Dispatchable generators can produce no more power in each hour than their nameplate capacity.

4. The amount of power transferred in each direction through each transmission line in each hour can be no more than the line’s rated capacity in that direction.

5. The flow of water through each hydroelectric dam must equal or exceed a pre-specified minimum level in each hour (this may be negative for pumped storage facilities).

6. The net flow of water through each hydroelectric dam each day must equal a pre-specified target level (this may be negative for pumped storage facilities).\(^8\)

7. The total supply of power in each load zone during each hour must equal or exceed the demand for power at that location and time, plus a 15 percent reserve margin. The supply of power includes the output from all intermittent renewable generators that have been installed (capacity installed * hourly capacity factor),

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\(^8\) These limits could instead be set on a weekly, monthly or annual basis, depending on the degree of flexibility available in operating the plant; the choice of daily limits is discussed further in the “Hydroelectric Plants” part of the “Data and Assumptions” section below.
active baseload plants (active baseload capacity \( \times [1 - \text{scheduled outage rate}] \)), the net power produced by hydroelectric facilities (power generated \( - \frac{1}{\text{round trip efficiency}} \times \text{power stored} \)), the power produced by all other dispatchable generators, and the net flow of power into the zone via transmission lines (sum \( \text{transmission efficiency} \times \text{transfers in} - \text{transfers out} \)). The total supply of power can exceed the demand for power, indicating that potential renewable or hydroelectric power is discarded unused during that hour.

**Expected-value planning** (these constraints apply to the expected-value version of the operational decisions):

8. Dispatchable generators can produce no more power in each hour than their nameplate capacity, prorated by their forced outage rate.

9. The amount of power transferred in each direction through each transmission line in each hour can be no more than the line’s rated capacity in that direction, prorated by its forced outage rate.

10. The flow of water through each hydroelectric dam must equal or exceed a pre-specified minimum level in each hour (same as constraint 5).

11. The net flow of water through each hydroelectric dam each day must equal a pre-specified target level (same as constraint 6).

12. The total expected supply of power in each load zone during each hour must equal or exceed the demand for power at that location and time, *with no reserve margin requirement*. The supply of power is calculated the same way as in constraint 7, but potential output from each baseload plant, hydroelectric facility or
intermittent renewable project is reduced by its forced outage rate, to obtain its output on an expected-value basis.

3.7 Treatment of Transmission Lines

The electric power system is one of the most complex systems that people have ever built or operated. Because of this complexity, models of the power system generally must choose between representing its electrical properties in great detail, but for only one moment in time, or representing its evolution over time, but with less electrical detail. The Switch model adopts the latter approach.

At one end of this spectrum lie security-constrained optimal power flow models. These are highly nonlinear models, which identify the least expensive dispatch plan for existing generators to meet a pre-specified set of loads, while maintaining adequate power quality and respecting constraints on the flow of power on every line in the network. These models require an estimate of the load on every bus in the system, and details on the capabilities of each generator and transmission line. They solve simultaneous equations representing the voltage and current at each bus and transmission line in the system, and in more advanced cases, they use complex terms to represent the flows of both real and reactive power in an AC system. The most sophisticated of these models also ensure that adequate power quality and stability can be maintained even if there is an unexpected outage of any line or generator in the system. These models are essential for the day-to-day operation of the grid (e.g., for managing power markets), and play a key role in determining how a proposed new generator, load or transmission line will affect the operation of the grid. However, because of their complexity and detailed data requirements, they can only be used to study a single case at a time (e.g., one hour or one
day’s worth of market operations, or the effect of a new transmission line with one pre-
specified set of loads and generators).

When modeling the long-term evolution of the power system, it is not possible
to treat the transmission network in as much detail as the optimal power flow models.
Instead, modelers use a simplified representation of the network, and focus their attention
on larger-scale balances of load, generator and transmission capacity, with a less de-
tailed representation of the power network. At the extreme of this approach, some long-
term studies ignore the network entirely, and focus only on the balance between genera-
tors and loads. A somewhat more sophisticated approach is taken by a number of long-
term models that use a “transport model” to represent the large-scale flow of power be-
tween different zones of a study area.\(^9\) A transport model assumes that it is possible to
choose how much electricity to send between any two regions, and requires only that the
supply of power from all generators can satisfy the demand for power at all load centers,
without overloading the transfer capability between any two regions. Such models give
up some detail of the behavior of the electric grid, but in exchange, gain the ability to
look at longer-term questions. This is the approach taken by the Switch model.

A transport model can be thought of as an abstraction of the coarse-scale capa-
bilities of the power transmission network, designed to approximate the ability of the
grid to move power between any two regions. It should not be thought of as an oversim-
plified network model, but rather as a separate class of model, designed to reflect the
general power-transfer capabilities of the grid, and the cost of increasing those capabili-
ties. One way to make this more clear is by distinguishing between the “transmission ca-
pacity” represented in power flow models, and the “transfer capability” used in transport

\(^9\) This is called a “transport model” because it is analogous to a model of the flow of cars or goods on a
road network.
models (Dobson et al. 2001; NERC 1996; WECC 2001). Transmission capacity refers to the thermal limits for specific, individual power lines. Transfer capability refers to the collective ability of all the lines in a power system to transfer power from one part of the network to another. In many cases, the transfer capability between two regions of a network may be less than the sum of the transmission capacity on the individual lines joining those regions, because some lines may become overloaded before others are saturated, or the system may not be able to saturate one line without risking instability if a line or generator fails.

Although a transport model is a simplifying abstraction, it may be useful for long-term planning, provided that the system’s initial “transfer capabilities” are represented accurately, and that the costs of upgrading “transfer capability” are recognized to be somewhat higher than simply building a single transmission line with an appropriate thermal limit between two points. Under these conditions, a transport model can provide at least a reasonable approximation of the cost of transmission upgrades needed to integrate new generators into the system, making an optimization of these costs possible. It can also provide useful hints about where additional transmission lines are likely to be needed. However, an optimization conducted using this approximation cannot be thought of as the final word on the cost or location of transmission upgrades needed in an optimal investment plan. It can give a rough idea, but detailed power flow studies of the proposed, “optimal” power system will be needed before the costs and reliability of the plan can be regarded with certainty.

That said, there are some reasons to believe that a transport model can be accurate enough for long-term planning. Zhao et al. (Zhao et al. 2006) note that increasingly sophisticated electronics allow for direct control of power flows on some transmission
paths, and this trend will increase in the future. Romero and Monticelli (1994) note that transport models generally identify 60–70 percent of the transmission investments upgrades that would be identified using a full network model. It should also be noted that there is some flexibility in the planning process, and if unbiased estimates are used for the cost of increasing transmission capability, then even if a transport-based plan does not identify exactly the right set of transmission upgrades, it should ultimately be possible to make a final transmission plan that does deliver the power as needed, within the costs that have been estimated.

There are several examples of long-term power planning models that use a transport model for the power network. The most relevant example for my work is the Prosym model, which was used to assess preferred long-term generation and transmission options for the 2007 Integrated Energy Policy Report (Jaske 2007). This model divides the western grid into 29 zones (10 in California), assesses the best way to dispatch a given set of generators distributed among these zones, and assesses which transmission corridors are likely to experience transmission congestion. Other production-cost models that use a transport network include POEMS, IPM, and ZPM (Eto et al. 2006).

### 3.8 Electricity Demand, Conservation and Energy Efficiency

Customers’ demand for electricity is not necessarily a fixed quantity – they may want consume more power if prices are low, or less if prices are high. This can happen either due to conservation (simply using less power when prices are high), or investment in energy efficiency measures. This effect is particularly pronounced over long time periods – if prices are persistently high over many months, customers have time to take notice and take action to reduce their consumption.
The Switch model represents this behavior via a step-wise demand curve. A user of the model first specifies base-case demand forecasts (in MWh) for every load zone, for every hour of the study. Then the user provides a series of demand curve “breakpoints” that describe a demand curve for electricity for the whole state, for each study period. Each breakpoint is defined by showing a percentage of the base-case demand, and a percentage of the base-case price. For example, one breakpoint could show a demand level of 0.9 and a price level of 1.2, then the next breakpoint could show a demand level of 0.95 and a price level of 1.1. This is interpreted as indicating that electricity customers would be willing to pay 120 percent of the base-case power price in order to consume electricity at levels between 90 and 95 percent of the base-case level. Then they would be willing to pay only 110 percent of the base-case price to consume 95 percent or more of their base case demand. The lowest and highest breakpoints indicate the lowest and highest amounts of electricity that customers can accept – i.e., the demand curve is assumed to become vertical at these points.

The demand curve is incorporated into the Switch model’s objective function as a measure of the benefit of providing electricity to customers (i.e., if they are only willing to buy a certain number of megawatt-hours of electricity at each price, then that must be the amount of benefit that they derive from those units of electricity). The total benefit is subtracted from the cost of producing power, and the model seeks to minimize this difference.

This benefit calculation is performed as follows: For each load zone and each study period, the model chooses what percentage of the base-case load will be satisfied. Then the model also chooses (independently) the total benefit that will be derived by customers from consuming this much power. A series of linear constraints ensure that
the “total benefit” level chosen by the model is at or below a “total benefit” curve, which is calculated by integrating the demand curve. (Since the demand curve is a series of flat, monotonically decreasing steps, the total benefit curve is a piecewise-linear, downward-convex curve.) Since the model's goal is to maximize the benefits of delivering power, this formulation ensures that the chosen benefit level will be exactly at the point on the total benefit curve corresponding to the chosen level of electricity demand.

These calculations apply for each multi-year investment period – the demand percentage chosen by the model is used to scale demand during all hours of that investment period, and the benefit is calculated as an average value across all hours of the study period, rather than varying from hour to hour. This approach is designed to reflect the ability and desire of customers to change their consumption in response to variations in annual average power prices.

For most of the work reported in this dissertation, a single breakpoint was specified, with a load and price of 100 percent, indicating that demand is completely inelastic at the forecast level. However, I did provide sloping demand curves for some sensitivity studies, investigating the effect of elastic demand and energy efficiency measures. These studies are described in sections 8.4 and 8.6.

3.9 Interruptible Load

The Pennsylvania-New Jersey-Maryland interconnect (PJM) and New England's Independent System Operator (ISO-NE) have recently allowed customers to offer interruptible load in their annual capacity auctions. To test whether interruptible load could be a useful part of the California power system, the Switch model incorporates a supply curve for interruptible load bids. Like the demand curve, this is specified as a se-
ries of steps. These steps indicate the percentages of load that would be willing to be cut, in exchange for a specified payment per kW-year. For example, customers may be willing to cut loads whenever called upon, by up to 1 percent of the peak level for a load zone, in return for a payment of $19 per year per kilowatt of committed load reduction, or they may be willing to cut up to 2% of the zone’s load in return for a payment of $38 per kilowatt per year.

To represent interruptible load bidding, the Switch model includes two additional sets of decision variables: one shows the amount of interruptible load that is committed in each load zone during each study period, and the second is constrained to equal or exceed the total cost of providing this capability in each zone (this cost is calculated as the integral of the interruptible load supply curve, up to the committed level of interruptible load). The total cost is incorporated into the main objective function, so that the model seeks to minimize this cost along with other costs of providing power. The committed amount of interruptible load is assumed to reduce reserve margin requirements during all hours (by an amount equal to the interruptible load, plus transmission losses, plus the reserve margin that would otherwise be used for that load), but has no other effect on system operation (i.e., load curtailments do not directly save enough fuel to be worth calculating). This formulation simplifies modeling, and reflects interruptible load’s role as a capacity-only commodity.

For most of the work discussed in this thesis, no interruptible load is assumed to be available. However, section 8.5 investigates the effect of interruptible loads on the design of the power system.
3.10 Topics that are not Directly Addressed by the Switch Model

3.10.1 Intermittency on the Sub-Hour Time Scale

The analysis presented in this dissertation suggests that as intermittent wind and solar power generators are added to the grid, they will slightly reduce the need for conventional generators to serve peak annual loads (i.e., long-term variations of the residual power demand). However, wind and solar generators are likely to add a great deal to the sub-hourly variation variation of the residual power demand to be served by conventional generators (Apt 2007; Curtright and Apt 2008).

The power spectra of conventional generators tend to ensure that any system that meets its long-term variations using them will also have ample capacity to meet sub-hourly variations in loads (i.e., on the regulation time scale) (Apt 2007; Curtright and Apt 2008). As a result, the system currently has excess capacity to serve these short term variations. However, as the system begins to use more renewables, this short-term variation could begin to exceed the regulation capacity of the remaining fossil plants. Even if this is not the case vis-à-vis the full fleet of conventional plants, it could still be a problem on an operational basis. That is, in the scenarios proposed by the Switch model, there are hours when most of the power comes from renewable resources, and few conventional generators provide power. Consequently, spinning reserves and regulation could be available in much more limited supply during these hours.

This suggests that more attention will need to be given to ensuring an adequate supply of regulation and spinning reserves. Options include keeping many more plants running at part load (which may have economic and environmental implications), de-loading renewable power facilities by 10–20%, so that they can be ramped up and down as needed, if the wind or loads fall or rise (Chowdhury and Rahman 1988; de Almeida et
al. 2006; Ekanayake et al. 2003), or pooling balancing services over a larger geographic area (Milligan and Kirby 2007, 2008). Another option could be to add more short-term storage to the power system. This is an area that has received less research than long-term storage, and there may be inexpensive options that could be developed on a large scale. Yet another option would be to develop markets for customers to respond to sub-hourly variations in the supply of power (Milligan and Kirby 2007, 2008), e.g., via automatic adjustment of air conditioner or refrigerator setpoints.

Although sub-hourly variations in the supply of power will be increasingly important in the high-renewable-energy futures suggested by the Switch model, I have not been able to quantify their effect on the power system as part of this work. This would be a fruitful direction for future research. One possibility would work along these lines: First use the work by Apt, Milligan and Kirby, and others to characterize the amount of sub-hourly variation associated with renewable power systems, and to identify how strongly correlated these variations are between nearby sites. Individual surges and lulls in wind speed or irradiance on a sub-hourly basis are likely to be uncorrelated between sites more than a few kilometers apart, because it is impossible for any disturbance to propagate through the atmosphere quickly enough to affect distant sites this soon. So it is likely that sub-hourly variation at any site can be simulated as an independent random process, and the variance at different sites will add in quadrature. However, it is likely that the variance at different sites will be correlated, even if the individual variations are not – i.e., weather patterns that produce highly variable winds or sunshine at one site are likely to produce similar conditions at other sites in the same region of the state. This information could be used to build a simple model of how much spinning reserve or dispatchable load must be obtained in order to firm up any given amount of wind or solar capacity on a
sub-hourly basis. That information could then be used in the Switch model to parameterize the need for these additional resources (either as standalone products, or as by-products of conventional power generators), so that their costs can be considered along with the capacity and energy values that are already included in the model.

3.10.2 Generator Ramp Rate Constraints and Partial Loading Inefficiency

The Switch model does not explicitly model the rate at which natural gas plants can ramp up and down. It simply assumes that the generators can be dispatched each hour at exactly the level that is needed. A review of capabilities for at least one combined cycle plant indicates that it can ramp up and down by about 2.5 percent of its rated capacity per minute, which means it can reach its full capacity in about 40 minutes. Simple cycle plants can ramp considerably faster (Katzenstein and Apt 2008). Kirby (2003) also notes that existing plants in California ramp up and down sharply as loads shift in early morning and late evening, with no discernible cost for the ramping service as distinct from the cost of the energy provided. He finds that existing power plants in the California ISO region have a ramping capability around 170 MW per minute, of which only 40 MW/minute has ever been used (Kirby and Milligan 2005 p. 7). These reports suggest that, on the hour-plus time scale that I use, ramp rate restrictions are not likely to be a binding constraint on the dispatch of combined cycle plants. It should be noted, however, that some of these plants may need advance notice in order to ramp up at these rates. The issue of short-term foresight is discussed in section 3.10.3.

The model also does not incorporate the additional cost of running plants at a level below their peak capacity, either to warm up, provide spinning reserves, or because not all of their capacity is needed. Katzenstein and Apt (2008) report that CCGT plants running at 5 percent of their nameplate capacity still use about half as much fuel as they
do when running at 100 percent of their nameplate capacity. A high-renewable system may need to operate fossil plants in their lower ranges more often, to prepare for unforeseen variations in renewable power output (on either a sub-hour or hour-plus time scale), so this could be an important omission. In the future I may extend the Switch model to incorporate parameterized requirements for spinning reserves or ramping capability (discussed in section 3.10.1), or to allow a warm-up period before drawing power from gas plants.

### 3.10.3 Long- and Short-Term Foresight

I assume in this work that it is possible to tell in advance exactly how much power will be needed on any given day and hour, so that power plants can be built during exactly the investment period when they are first needed, and power plants can be dispatched exactly when loads or renewable power supplies rise or fall.

Long-term foresight may not be a large oversimplification, since power planners already have experience forecasting peak loads, experience which may be readily extended to cover peak residual loads, including the effect of renewable power. The system also includes a substantial reserve margin, in case of unexpected conditions, and, as will be discussed below, generally includes enough conventional resources to meet peak loads with very little reliance on renewables.

Short-term foresight may be a more serious omission. Forecasting of output from renewable power systems is improving constantly, and appears to be easier for a system with widely dispersed renewable resources (as envisioned here), rather than a single wind farm. This problem is also not fundamentally different from the daily forecasting of electricity loads. However, in a system that relies heavily on intermittent renewable resources, forecasting will be an important factor. It remains to be seen whether forecast-
ing will be good enough to make as efficient use of renewable resources as I suggest here, or whether additional fossil plants will need to be kept as spinning reserves, in case of a mis-forecast. This question overlaps some with the issues of sub-hour intermittency and generator ramp rate constraints – in all cases, the answer may be to keep more spinning reserves available or develop more short-term power markets or storage.

Given the uncertainty about the clarity of short-term foresight, the results of the Switch model should be considered a target to shoot for, rather than a guaranteed outcome — this is what is possible if we can make efficient use of renewable and conventional plants.

3.10.4 Indirect Effects of Power System Investment and Operation Choices

3.10.4.1 Cost of Inputs

The Switch model does not endogenously consider the effect of investment decisions on the market price of fuel and equipment – it is assumed that unlimited purchases can be made without raising prices (through elevated demand) or lowering them (through economies of scale or learning-by-doing). With the current design of the Switch model, the best way to address these effects is to run the model repeatedly with different price forecasts, until the forecasts are consistent with the investment decisions (there may be multiple consistent sets of forecasts and investment plans, corresponding to different path dependencies, e.g., “high dependence on natural gas,” “high dependence on photovoltaics,” “balanced use of wind and solar,” etc.).

3.10.5 Detailed Power Flow and Comprehensive Set of System States

As noted in sections 3.1, 3.7 and 4.2, the Switch model does not include a complete treatment of the electrical properties of the transmission network, nor does it op-
timize over all possible weather conditions. Consequently, confidence in its findings rests heavily on the assumption that the transport model it uses is a reasonably accurate representation of the capabilities of transmission network, and that the limited number of states it samples are a reasonably accurate representation of the range of possible conditions that could be encountered by the power system. As discussed in those sections, these appear to be reasonable assumptions, and it is likely that the investment plans proposed by the Switch model are more optimal than a “business-as-usual” case might be (e.g., investment only in natural gas CCGT plants). However, power system planners would be right to regard this claim with some skepticism, until it can be tested against a more detailed representation of the power network and a wider range of system conditions.

Rather than attempt to include these additional details in the optimization module, I plan in the near future to add an additional “tweak and test” module to the Switch model, to test the performance of the proposed investment plan with a full power flow model, and a wider range of system states.

The new module will begin with a proposed investment plan, either from the Switch model, or a heuristically developed “business-as-usual” case. It will first convert this investment plan into a more detailed representation of the California power system – new “transfer capability” between zones will be made specific, in the form of new transmission lines between particular points on the existing network; and proposed new generators will be added at specific points on this network.

A large set of potential future state-wide weather conditions will then be generated, based on historical conditions, but possibly also including extreme weather events beyond the range shown in the available historical data. This set could include several
hundred days of data, selected either via simple random sampling from the range of possible conditions, or stratified sampling to represent the full range of possible conditions.

The new module will then run an adequacy test – using an optimal power flow model with this proposed set of generators and transmission lines, during each of these simulated dates. If the system is unable to meet loads reliably, the investment plan will be adjusted via a simple deterministic rule – e.g., adding natural gas capacity in the region where the power supply falls short – and the adequacy test will be repeated, until the system is reliable enough. I do not anticipate that these adjustments will radically change the makeup or cost of the investment plan, but they will convert it to a similar form that is known to be reliable with more certainty.

Finally, the same framework will be used to test the cost of using the adjusted version of the Switch investment plan, versus an alternative, business-as-usual case. If, as is expected, the cost of the Switch plan is lower than the business-as-usual plan, it will lend much more credence to the claim that we should be using that plan.

In this enhanced version of the Switch model, the existing optimizer module will have the role of finding a “near-optimal” investment plan, but the testing module will then test this plan against alternative (or business-as-usual) cases using more traditional power planning methods. As a result, power system planners will be able to have greater confidence that the proposed plan is an improvement, without necessarily putting their faith in the skill of the optimizer module itself.

3.10.6 Policy Context

The Switch model uses an exogenously specified carbon cost, then minimizes the total cost of delivering power, while ascribing this cost to all carbon dioxide emissions.
This cost could correspond to a carbon tax, the market price of permits under a cap-and-trade system, or an analytical adder to reflect social cost.

This system could be developed either via a cost-based, centralized planning approach, similar to traditional utility integrated resource planning, with carbon dioxide adders, and more coordination among investor-owned and publicly owned utilities than has historically been the case. Or it may be possible to achieve this outcome under a market-based system, with an explicit carbon dioxide tax, cap-and-trade system or renewable portfolio standard. Either way, the system proposed by the Switch model should achieve the lowest average power bills for ratepayers, with one important caveat. Under a market-based system, there may be scarcity rents for resources available in limited amounts, such as good wind sites, hydroelectric facilities, or existing power plants and transmission lines. The Switch model does not account for the effect of these on power prices.

It is also not clear that deregulated power markets could ever be fluid enough (and free enough of anti-competitive behavior) to naturally find their way to an optimal power system design on the basis of a carbon dioxide tax (or similar mechanism) alone. For example, utilities may be reluctant to adopt unfamiliar technologies, or may not be confident that added costs for carbon dioxide will persist over the long term.

In this thesis, I do not advocate any particular political approach to developing an optimal power system. Instead, I seek to elucidate what might be included in an optimal power system, which I hope will open the way to further discussion of what will need to be done in order to build such a system.
CHAPTER 4: DATA AND ASSUMPTIONS

4.1 Discount and Finance Rates

For the work reported here, a real discount rate of 3 percent has been assumed for all future costs, corresponding to a nominal rate of about 6 percent. The finance rate for transmission lines and central-station generators is assumed to be 6 percent (~9 percent nominal). This is intended to represent the cost that would be incurred in any effort to develop an optimal power generation portfolio for California ratepayers collectively (i.e., funded by regulated utilities or state-sponsored bonds). It does not reflect the higher rates of return that would be needed to induce private companies to build power plants with no guarantee of repayment. Rooftop photovoltaics use a finance rate of 3 percent (~6 percent nominal), which represents low-cost financing available via municipal bond programs (e.g., the recent Berkeley solar initiative), or federally-subsidized interest on home-equity loans.

4.2 Study Years and Hours

For the work reported here, the Switch model uses four four-year investment periods, beginning in 2010, 2014, 2018 and 2022. Twenty-four historical dates are chosen to represent environmental conditions during each investment period. These are made up of two dates for each month of the year: one chosen at random, and one representing a peak-load day. All of these historical dates are chosen from the range of November 2002 through October 2004. For example, the 2014 study period includes conditions from one randomly chosen October day (10/11/2003), and from the October date with the highest peak load (10/21/2003) in this two-year period. Conditions on the peak day are re-used for all four investment periods. This sampling method ensures that investment choices provide adequate reserves for the peak load day each period.
Because fewer days are sampled than the actual length of each investment period, each sampled date is weighted to represent multiple study days during the period. For example, for the work reported here, the 2014–2017 study period contains 124 October days, but is represented by only two sampled dates. I give each hour of the “random” day a “weight” of 122, to indicate that it represents 122 October days; all expenditures on fuel and carbon costs during this date are multiplied by this factor during the economic analysis. The peak day is given a weight of 2, since these conditions occur less often.\textsuperscript{10} This weighting system ensures that high-stress conditions are included in the reliability constraints, but “typical” conditions (represented by the randomly selected day) predominate in the economic assessment of operational decisions.

### 4.3 Load Zones

For the work reported here, the state of California is divided into 16 “load zones,” shown in Figure 1. Several factors make this a natural scale to divide the state: (1) These regions correspond closely to the “load pockets” traditionally used for reliability analysis in California – they are well-connected internally, but sometimes suffer from congested transmission to neighboring zones; (2) historical hourly electricity loads have been recorded and made publicly available for these regions (and not on any finer scale); (3) this scale is fine enough to reflect much of the geographic diversity of the state; and (4) there are few enough regions that they can be represented in an optimization model which is solvable in a reasonable period of time.

Thirteen of these zones are subdivisions of the region managed by the California Independent System Operator (CAISO), and the remaining three are the service areas of

\textsuperscript{10} The peak day has a 1-in-62 chance of occurring (since there are 62 October dates in the 2002–2004 period from which it is drawn), so it is given a weight of $\frac{124}{62}=2$. The non-peak dates have a $\frac{61}{62}$ chance of occurring, so they receive a weight of $124\times\frac{61}{62}=122$. 
the public utilities serving Sacramento, Los Angeles and the Imperial Irrigation District. Electric utilities based in other states serve some less-populated parts of northern California, and these are omitted from this study. There are also two “virtual” zones corresponding to power supplies available for import from northwestern and southwestern states into the other 16 study zones.

![California electricity load zones](image)

*Figure 1. California electricity load zones*

A model with a finer geographic scale would give a clearer picture of the state’s transmission needs, but is not possible with publicly available load data, and probably could not be solved on current desktop computers. The scale I have chosen may nevertheless give a reasonably clear picture of how power could be moved throughout the state.
A wider geographic range would also be useful, in order to incorporate interactions with the rest of the WECC; unfortunately, that is also infeasible within the scope of this project. Relying primarily on in-state resources probably makes my findings more conservative, since it foregoes the possibility of exchanging loads and resources with nearby regions, which could provide additional low-cost renewable resources and/or help to smooth over variations in the supply and demand for power in California.

4.4 Baseline Electricity Loads

The hourly profile of electricity loads in each load zone for each sampled day are estimated based on historical hourly measurements reported in two publicly available databases. The California Independent System Operator reports hourly electricity loads for 12 “load aggregation areas” for November 2002 through April 2005, as part of a series of studies on location-specific pricing of electricity in a future upgrade to their market software (CAISO 2007). By design, eleven of these load aggregation areas map directly onto load zones in the Switch model. However, in order to create a more geographically realistic simulation, I divide the CAISO’s “Other PG&E” area into two separate regions – “PG&E North” and “PG&E South.” I assign 47.6% of the “Other PG&E” load to the “PG&E North” area and 52.4% to the “PG&E South” area, based on load distribution factors reported for individual buses in each zone (CAISO 2007). The three remaining load zones correspond to California’s three public electric utilities; their loads were obtained from annual filings of FERC Form 714 for 2002–04 (FERC 2005).

Each future day in the Switch model corresponds to one real, historical day. In order to obtain loads for this future day, loads from 2002–04 are scaled up to match forecasts of the peak and average annual load for future years. These forecasts are derived from the California Energy Commission’s zonal demand forecast for 2008–18 (Marshall
and Gorin 2007), which escalate linearly over time. I then extended this linear trend for years beyond 2018. Table 2 shows the average and peak loads in each load zone in 2004, and the average annual growth rates from then until 2022.

For most of the work reported here, electricity loads are fixed at these levels. However, in sections 8.4 and 8.6 I consider some scenarios where loads are reduced dynamically in response to higher power prices.

Table 2. Electricity loads and annual growth rate in each load zone, 2004–22

<table>
<thead>
<tr>
<th>Load Zone</th>
<th>2004 Average Load (MW)</th>
<th>2004 Peak Load (MW)</th>
<th>Annual Growth of Peak Load (linear)</th>
<th>Annual Growth of Average Load (linear)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Humboldt</td>
<td>98</td>
<td>142</td>
<td>1.7%</td>
<td>2.5%</td>
</tr>
<tr>
<td>North Coast</td>
<td>130</td>
<td>231</td>
<td>1.7%</td>
<td>2.5%</td>
</tr>
<tr>
<td>Geysers</td>
<td>315</td>
<td>511</td>
<td>1.3%</td>
<td>2.4%</td>
</tr>
<tr>
<td>PG&amp;E North</td>
<td>1,936</td>
<td>3,319</td>
<td>1.6%</td>
<td>2.3%</td>
</tr>
<tr>
<td>San Francisco</td>
<td>795</td>
<td>1,146</td>
<td>0.8%</td>
<td>0.3%</td>
</tr>
<tr>
<td>Other Bay Area</td>
<td>4,255</td>
<td>7,002</td>
<td>1.0%</td>
<td>1.5%</td>
</tr>
<tr>
<td>Sierra</td>
<td>264</td>
<td>558</td>
<td>1.8%</td>
<td>2.7%</td>
</tr>
<tr>
<td>PG&amp;E South</td>
<td>2,133</td>
<td>3,658</td>
<td>1.8%</td>
<td>2.6%</td>
</tr>
<tr>
<td>Fresno</td>
<td>1,326</td>
<td>2,634</td>
<td>2.0%</td>
<td>1.8%</td>
</tr>
<tr>
<td>ZP26</td>
<td>1,053</td>
<td>1,790</td>
<td>1.7%</td>
<td>2.0%</td>
</tr>
<tr>
<td>Other SCE</td>
<td>9,307</td>
<td>16,280</td>
<td>1.8%</td>
<td>1.7%</td>
</tr>
<tr>
<td>Orange</td>
<td>2,888</td>
<td>4,928</td>
<td>1.1%</td>
<td>0.9%</td>
</tr>
<tr>
<td>San Diego</td>
<td>2,353</td>
<td>4,088</td>
<td>1.7%</td>
<td>2.2%</td>
</tr>
<tr>
<td>Sacramento</td>
<td>1,245</td>
<td>2,672</td>
<td>1.8%</td>
<td>2.4%</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>3,045</td>
<td>5,418</td>
<td>0.6%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Imperial</td>
<td>391</td>
<td>840</td>
<td>3.6%</td>
<td>3.6%</td>
</tr>
</tbody>
</table>

11 The Energy Commission’s load zones do not match exactly with the Switch model’s zones. So I assigned their forecasted loads to my zones by overlaying the two maps, then assigning fractions of each of the Energy Commission’s zones to the Switch zones, proportional to the population of their intersecting areas.
4.5 **Baseline Electricity Prices**

For parts of this work, I have used a sloping demand curve for electricity. This demand curve is specified in generic terms showing the percentage change in electricity consumption, in response to a percentage change in electricity price. This curve must then be positioned by a baseline electricity load and price for each load zone. The baseline loads were described in section 4.4. Here I describe the calculation of the baseline electricity price. It should be noted that this price only has an effect on electricity consumption in cases where a sloped demand curve has been used. When a vertical demand curve is used, the level of power consumption is fixed, regardless of the cost of providing the electricity.

Baseline loads in the Switch model are based on the California Energy Commission's demand forecast for 2008-18 (Marshall and Gorin 2007). The authors of that study report that their forecasts assume power prices are the same in future years as they were in 2005. It is difficult to find out what their perception is of the cost of power in 2005, or to match that with the power costs calculated internally by the Switch model (for example, Marshall and Gorin use load zones with somewhat different boundaries than the Switch model, and the power costs they identified likely included billing costs or other adders that are not included in the Switch model). So, rather than attempting to find a specific relationship between Marshall and Gorin's estimates of power prices and the Switch model's calculation of power costs, I instead use the Switch model to calculate its own estimate of marginal cost of power in each load zone in 2005. I then assume that there is a fixed (though unknown) ratio between the retail price faced by consumers and the Switch model's annual average power costs. For example, if the Switch model's all-in cost of power in 2022 is 25 percent higher than in 2005, I assume that retail prices of the sort used by Marshall and Gorin would also be 25 percent higher than they were in
2005. So then it is possible to use the Switch model’s estimate of 2005 power prices as the baseline for elastic demand curves in future years.

The Switch model’s power prices for 2005 were calculated as follows: I first applied a vertical demand curve, fixing power consumption at 2005 levels. I then ran the Switch model, using power plants that existed in 2005, fuel prices from 2005, and allowing construction of no new plants. This produced an optimal plan for using the generation and transmission fleet, as it existed in 2005. I then calculated the marginal cost of power in each load zone by inspecting the dual value of the fixed level of demand. For example, I found that if year-round loads in Fresno were reduced by a total of 1 MWh (with a temporal profile identical to the average load for Fresno that year), the system could save $82.98. Similar values were found for all other load zones. These indicate the marginal cost of supplying year-round power to “average” customers in each load zone. I then use these values as the baseline price for the future demand curves, so that if power can be provided at a lower marginal cost than it was in 2005, more will be generated, and if power costs more to produce than in 2005, less will be provided. The marginal cost of power for each load zone is shown in Table 3.
Table 3. Baseline cost of power in each load zone, 2007$/MWh for annual load with typical temporal profile

<table>
<thead>
<tr>
<th>Load Zone</th>
<th>Baseline Power Cost (2007$/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fresno</td>
<td>$82.98</td>
</tr>
<tr>
<td>Geysers</td>
<td>$76.54</td>
</tr>
<tr>
<td>Humboldt</td>
<td>$85.02</td>
</tr>
<tr>
<td>Imperial</td>
<td>$82.90</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>$81.05</td>
</tr>
<tr>
<td>North Coast</td>
<td>$78.00</td>
</tr>
<tr>
<td>Orange</td>
<td>$84.39</td>
</tr>
<tr>
<td>Other Bay Area</td>
<td>$84.90</td>
</tr>
<tr>
<td>Other SCE</td>
<td>$81.58</td>
</tr>
<tr>
<td>PG&amp;E North</td>
<td>$81.00</td>
</tr>
<tr>
<td>PG&amp;E South</td>
<td>$81.32</td>
</tr>
<tr>
<td>Sacramento</td>
<td>$85.42</td>
</tr>
<tr>
<td>San Diego</td>
<td>$83.00</td>
</tr>
<tr>
<td>San Francisco</td>
<td>$89.23</td>
</tr>
<tr>
<td>Sierra</td>
<td>$83.87</td>
</tr>
<tr>
<td>ZP26</td>
<td>$77.43</td>
</tr>
</tbody>
</table>

4.6 Capital Cost and Other Properties of New Power Plants

The Switch model can install five different types of generator at the beginning of each study period: gas-fired combined cycle combustion turbines, gas-fired simple-cycle combustion turbines, wind farms, distributed solar photovoltaic modules, or solar thermal troughs.

The current-day capital costs of natural gas, wind and solar-thermal plants are derived from the California Energy Commission’s cost-of-generation study (Klein and Rednam 2007). Current-day capital costs for new photovoltaic power systems are found by averaging the costs shown in the California Energy Commission’s database of all sys-
tems that received rebates in 2006 (CEC 2007b). Future capital costs of each technology are projected from these current costs, using an exponential rate of decline, based on historical cost trends over the longest recent periods reported in the literature (Colpier and Cornland 2002; Navigant Consulting 2007a; Neij et al. 2003; Nemet 2006; Wiser et al. 2006). The current costs and rate of change for each technology are shown in Table 4. Table 5 shows the projected capital cost for new plants of each type built during the four study periods.

Information on the efficiency, operating cost and forced-outage rate of existing plants is obtained from the same sources as the current-day capital cost.
Table 4. Capital cost of new California power plants

<table>
<thead>
<tr>
<th>Technology</th>
<th>Capital Cost in 2005 or 2006 ($/kW)</th>
<th>Rate of Change of Real Capital Cost (%/year)</th>
<th>Source of Current Capital Cost Data</th>
<th>Source of Capital Cost Trend Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Combined Cycle Gas Turbine</td>
<td>$752</td>
<td>−1.6%</td>
<td>(Klein and Rednam 2007)</td>
<td>Contract prices reported by all major manufacturers in trade journals, 1981–97 (Colpier and Cornland 2002)</td>
</tr>
<tr>
<td>Simple Cycle Gas Turbine¹²</td>
<td>$928</td>
<td>0.0%</td>
<td>(Klein and Rednam 2007)</td>
<td>No data available; widely regarded as a mature technology, with static costs.</td>
</tr>
<tr>
<td>Wind Farm</td>
<td>$1,900</td>
<td>−3.5%</td>
<td>(Klein and Rednam 2007)</td>
<td>Turnkey costs of wind farms in Sweden and Denmark, 1980–2000 (Neij et al. 2003)</td>
</tr>
<tr>
<td>Distributed Photovoltaics</td>
<td>$9,190</td>
<td>−4.8%</td>
<td>(CEC 2007b)</td>
<td>Installed systems in California, 1998–2005 (Wiser et al. 2006); a nearly identical trend held for global module prices, 1987–2003 (Nemet 2006)</td>
</tr>
<tr>
<td>Solar Thermal Parabolic Trough (no storage)</td>
<td>$3,900</td>
<td>−3.6%</td>
<td>(Klein and Rednam 2007; Navigant Consulting 2007b)</td>
<td>Projections for 2010–25, for solar troughs with storage, based on industry interviews (Navigant Consulting 2007a)</td>
</tr>
</tbody>
</table>

Table 5. Projected capital cost of new generation plants (2007$/kW)

<table>
<thead>
<tr>
<th></th>
<th>CCGT</th>
<th>DistPV</th>
<th>Trough</th>
<th>Wind</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>$694</td>
<td>$7,549</td>
<td>$3,368</td>
<td>$1,648</td>
</tr>
<tr>
<td>2014</td>
<td>$650</td>
<td>$6,200</td>
<td>$2,909</td>
<td>$1,429</td>
</tr>
<tr>
<td>2018</td>
<td>$610</td>
<td>$5,093</td>
<td>$2,512</td>
<td>$1,239</td>
</tr>
<tr>
<td>2022</td>
<td>$572</td>
<td>$4,183</td>
<td>$2,169</td>
<td>$1,074</td>
</tr>
</tbody>
</table>

¹² It is unusual to see higher prices quoted for simple cycle plants than for combined cycle; I am investigating this issue and may use different costs for future analyses.
4.7 **Interconnection Costs for New Power Plants**

The cost of connecting new power plants to the electric grid is estimated as follows.

I assume that new central-station fossil plants can be built near a major interconnection point. Consequently, the cost of connecting them is only average the “linear” cost of connection that Klein and Rednam (2007) found in surveys of recently built power plants. This is $64/kW for CCGT plants and $10/kW for simple cycle plants.

I assume that transmission lines must be built from each wind farm site to the nearest interconnection point reported by the state’s three investor-owned utilities in the CPUC-mandated Transmission Ranking Cost Reports (TRCRs) (PG&E 2007; SCE 2007; SDG&E 2007). These lines are assumed to cost the same as inter-zonal transmission lines ($1,000/MW-km or $1/kW-km). I also assume that the cost of intra-grid upgrades to support each of these interconnections is proportional to the largest upgrade considered in the TRCR for that location. For example, SCE’s TRCR indicates that up to 8.4 GW can be connected to its new Tehachapi substations, at a total cost of $2.6 billion, so I assume that it will cost $2.6 B / 8.4 GW, or $311 per kW to connect any new wind farms there, in addition to the cost of building a transmission line from the wind farm to the substation. The interconnect points and costs for each wind resource area are shown in Table 6. I did not consider connecting wind farms to non-IOU parts of the California power system, because all of the wind farms studied in the Intermittency Analysis Project are reasonably close to IOU interconnect points.
For solar thermal electric troughs, I assumed that a transmission line must be built from the hypothetical solar project location (i.e., the CIMIS monitoring site) to the nearest 230 kV or higher substation in the power system. These lines are also assumed to cost $1/kW-km. I further assumed that grid upgrades at the interconnect point would have a cost equal to the average among all interconnect points reported in the IOU TRCRs. This amounts to $233 per kW.

I do not assume any interconnect cost for distributed photovoltaic systems, and indeed, these systems are assumed to reduce the need for intra-zone upgrades, if they help reduce the peak electric load within their zone (see section 4.11).
4.8 Existing Power Plants

4.8.1 Natural Gas, Coal, Nuclear and Geothermal Plants

Data on the size, technology, location, ownership and operational mode of all existing power plants in California were obtained from the Energy Information Administration's power plant survey databases for 2006 (EIA 2007a, 2007b). The same information was also obtained for several power plants in Arizona, New Mexico and Nevada, that are partially owned by California electric utilities, and capable of delivering power to California. For this study, the power-generating capacity of the out-of-state plants has been prorated according to the share of the plant owned by California utilities; i.e., they are treated as smaller plants that can be operated as needed to serve California electricity loads. In all, the model uses data on 270 existing natural gas, coal, nuclear and geothermal plants, with a combined peak output of 44 GW.

Power plants are categorized based on their fuel and mode of operation. All nuclear, coal and geothermal power plants, as well as gas-fired cogeneration plants, are assumed to operate in a baseload mode, year round, producing as much power as they did on average in 2002–04. The remaining gas-fired power plants are assumed to be dispatchable as needed, and the model chooses each hour whether or not to operate them.

All nuclear, coal and geothermal power plants, as well as gas-fired cogeneration plants, are assumed to be capable only of operating in baseload mode, year round, producing as much power as they did on average in 2002–04. The remaining gas-fired power plants are assumed to be dispatchable as needed.

The efficiency of most existing power plants was calculated by dividing their net power generation in 2002–04 by the amount of fuel that they consumed during the same period. It is assumed that they will operate with the same efficiency any time they are
used in the future. However, the EIA surveys do not collect enough data to determine
the electrical efficiency of cogeneration facilities. For this study, it is assumed that these
plants are 75 percent efficient in converting fuel into steam heat and electricity, and that
if necessary, they could instead produce only steam, also at 75 percent efficiency (EPA
(2005) shows thermal efficiencies of 56–86 percent for typical cogeneration plants).
These two assumptions yield a marginal efficiency for production of electricity that is
also 75 percent.

Existing natural gas power plants are assumed to have the same operating costs
and forced outage rates as new plants of the same type. However, cogeneration plants are
assumed to cost three-quarters as much as free-standing power plants, to reflect the
sharing of costs with steam infrastructure that would be needed even if no electricity
were produced. Costs for coal, nuclear and geothermal plants are based on assumptions
to AEO.

Forced outage rates of existing natural gas plants are assumed to be the same as
those given for new plants in the CEC’s cost of generation study. Other plants are as-
sumed to have a 1 percent forced outage rate.

Retirement ages for existing coal, gas and nuclear plants are estimated by averag-
ing the retirement age of similar plants that have already been retired, as shown in the
EIA databases (EIA 2007a). No retired geothermal plants are shown in the EIA data-
bases, so binary turbine plants are assumed to have a retirement age of 30 years (5 years
longer than natural gas turbines in the EIA database), and geothermal steam turbines are
assumed to last 45 years, corresponding to other steam turbine plants.
4.8.2 Hydroelectric Plants

Hydroelectric power plants and pumped-storage facilities in California operate under complicated dispatch rules that balance needs for in-stream flows, water storage, flood control capability and power production. Many California reservoirs are small, only holding several days of water flow. For others, it is unclear how much flexibility system operators have in rescheduling power dispatch between different months, or different days of the month. The Switch model uses two constraints to represent these limits in a simplified manner: (1) On any future date in the simulation, each dam must release as much water as it released on average during the historical month corresponding to that date (e.g., on a simulated date in 2021, which uses weather conditions from March 20, 2003, each dam must release 1/31 as much water as it did during the month of March 2003). (2) During each hour of the day, hydroelectric facilities must release at least 10 percent of the required average flow rate for that day, to provide for in-stream water flows. The second constraint does not apply to pumped storage facilities, which are able to reverse the flow of water at times, to store energy for future use.

There are several reasons for formulating the hydro net flow constraints on a daily basis, instead of weekly, monthly or longer scale. (1) Limited data are available on the availability of water and storage on a sub-monthly time-scale. Using the same constraints for every day of the month is a conservative approach, which is guaranteed to yield the monthly average flows that have occurred historically. (2) In order to model storage and dispatch of water between any two periods, both periods must be included in the Switch model. Since the model only includes one date from each month, it is not possible to model storage of water over periods of longer than one day, e.g., from one week to the next. (3) Many of California’s reservoirs have limited storage capacity, so that it may be unrealistic to plan to store more than a day’s worth of water in them.
The model chooses how much power to generate in each hour, from each hydroelectric dam larger than 50 MW, subject to these constraints. Smaller hydroelectric plants are assumed to run in a baseload mode, supplying the same amount of power for every hour of the day. Pumped hydroelectric storage facilities are assumed to have an 80 percent round-trip efficiency.

Plant sizes, locations and historical water flows are derived from databases published by the Energy Information Administration and the United States Geological Survey (EIA 2007a, 2007b; USGS 2007). An additional “virtual” hydroelectric plant is added in the Northwest load zone, to represent hydroelectric power available for import to California from the Northwest. The monthly flow limits for this plant are based on historical power transfers, as reported by the Northwest Power Pool (NWPP 2007).

In all, the model simulates the operation of 63 large hydroelectric plants, with a nameplate capacity of 21.8 GW and an average power production of 5.7 GW. There are also 186 smaller plants, with an average power output of 0.74 GW.

4.8.3 Wind, Solar and other Generators

Existing wind, solar, and biomass/waste generators are not included in the modeling work discussed here, although they may be incorporated into a future version of the Switch model. Wind farms provided about 1.8 percent of California’s electricity in 2006; if incorporated into the model, they would be expected to reduce new installations of wind equipment by a similar amount, maintaining the same total amount of wind power capacity. Biomass and waste-powered generators supplied 2.1 percent of California’s electricity in 2006. These would be expected to displace an equal amount of new gas-fired capacity from the model, or possibly add more baseload capacity, reducing the use of both renewable and natural gas resources. Solar power generators supplied a negligible
share of the state’s power in 2006, but the California Solar Initiative, announced in 2006, provides incentives to install enough photovoltaic equipment by 2017 to raise this share to about 1.5 percent (3 GW nameplate). These systems would be expected to displace a similar amount of solar photovoltaic or solar thermal-electric generators from the model results shown here.

4.9 Wind Speeds and Solar Irradiance

4.9.1 Wind Resources

The location, size and hourly power production from potential wind power sites are based on research done by AWS Truewind to support the California Energy Commission’s Intermittency Analysis Project (Brower 2007; Porter and IAP Team 2007a).

The Intermittency Analysis Project (IAP) was a collaborative effort by the CEC, the California Wind Energy Collaborative, AWS Truewind, and GE Energy Consulting (check name), to assess the impacts of using large amounts of wind power in the California power system. For this project, the CEC and Truewind identified 3 regions with existing wind farms, and 11 additional regions of interest for future wind power development (Figure 5). Truewind divided each of these regions into grids with 200 meter spatial resolution. They excluded any grid squares that were in federal or state forests or parks, within 1 mile of a populated area, or had slopes steeper than 20 percent. Truewind then calculated the expected cost of producing electricity from wind turbines in each cell, based on the annual average power production (from a previous modeling effort (Brower 2002)), and an assessment of the cost of connecting each cell to the existing transmission network. Finally, Truewind identified wind-farm-sized clusters of cells that could provide power below a minimum cost threshold. Truewind adjusted the cost threshold until the screening yielded 302 sites, which could produce up to 34 MW of power. Truewind
then worked with other project participants to narrow this list to 57 sites (2100 MW) that have already been developed, 42 sites (5900 MW) that are good candidates for development by 2010, and 134 sites (14,800 MW) that could be developed in 2020. The details of this “whittling down” process are not readily available, but it is clear that the IAP’s goal was to produce a plausible portfolio of wind sites that could be developed under a 33 percent RPS by 2020, rather than to identify the best possible sites, or to assess all promising wind sites in the state (Brower 2007; Yen-Nakafuji 2007). Truewind then used mesoscale and microscale numerical weather models to estimate the power that could have been produced at each existing or potential wind farm site during every hour of 2002–04.

This effort produced the richest available dataset of the hourly performance of a large number of wind farms throughout California. However, the IAP’s pre-screening techniques make it difficult to use these data as the basis for my research: (1) This study included more wind sites than any previous effort, but nevertheless excluded many wind sites that could be economically viable, especially as the cost of wind turbines falls. Consequently, relying only on their dataset will give an artificially low estimate of the amount of wind power that could be developed in California. (2) The IAP study assumed that current models of wind turbine would be used at the sites developed in 2010, and new, more efficient models would be used in 2020. This makes it difficult to assess how the 2020 sites would perform if they were developed in 2010 and vice versa.

In the next two sections, I discuss techniques that I used to expand the IAP dataset to be closer to the total size of California’s wind resources, and to undo their assumptions about which sites would be developed in which year.
4.9.1.1 Reversing IAP’s Assumptions About Technological Evolution

As noted above, the IAP study made \textit{a priori} assumptions about which wind sites would be developed around 2010, and which would be developed around 2020, and it assumed that wind turbines installed in 2020 would be more efficient than 2010. However, one goal of the Switch model is to identify which sites should be developed when. So I have de-rated all the 2020-vintage sites in the IAP dataset, to estimate the power they would produce if they were developed in 2010 instead. I then use the 2010-vintage power production for all new sites, regardless of when they are developed. This introduces some extra conservatism to my analysis, because sites developed later in the study could actually produce more power per hour than I assume.

To adjust wind speeds for each 2020-vintage site, I first identified the turbine model that the IAP assumed would be used at that site, and then applied a simple multiplier to estimate the power output that would have come from a corresponding 2010-vintage turbine. The rest of this section explains this process.

Figure 2 shows the power curves that the IAP used to estimate power production by each wind turbine, based on hourly wind speeds. For sites developed in 2010, they used curves corresponding to wind turbine models available today; for 2020, they used curves corresponding to improved turbines (Brower 2007). The IAP authors assigned each site to an IEC wind class based on its annual average wind speed, and used different turbine models for each class. Class 3 sites have annual average wind speeds below 7.5 m/s, class 2 sites are between 7.5 and 8.5 m/s, and class 3 sites have annual average wind speeds above 8.5 m/s. The IAP authors did not report wind speeds or IEC classes for individual sites. So, I first used the power curves from Figure 2 to estimate hourly wind speeds at each wind farm, based on the reported power output. I then identified the IEC class corresponding to the deduced annual average wind speed for each wind farm.
Figure 2. Wind turbine power curves used in the Intermittency Analysis Project

Figure 3. Ratio between power production by 2010 and 2020 IAP turbine models

Figure 3 shows the ratio between the power production by 2010 and 2020 turbine models, for each IEC class. These are the ratios between the two lines shown in each plot of Figure 2. The 2010 models of the class 1 and 2 turbines generally produce about 90 percent as much power as the corresponding 2020 model, when wind speeds are below about 12 m/s. The 2010 class 3 turbine produces about 70 percent as much power as the 2020 model in this wind speed range. The older models and newer models produce the same amount of power when wind speeds are above this range; however, since the IAP does not report wind speeds directly, when the 2020 turbines are producing 100 per-
cent of their rated power, it is impossible to know whether the 2010 model would also do so, or whether wind speeds are in the 10–12 m/s range, where the 2010 models underperform the 2020 models. Wind farms in the IAP dataset produce their rated output less than 1 percent of the time, so this issue may not be very important. Consequently, I assume that a 2010 class 1 or 2 wind farm produces 90 percent as much power as a 2020 wind farm during all hours, and that a 2010 class 3 wind farm produces 70 percent as much power as a 2020 version, at all times. By inspection of Figure 3, it is clear that these are conservative estimates of the power output from 2010-vintage wind farms.

4.9.1.2 Additional Low-Speed Wind Sites

In early runs of the Switch model, I found that it fully developed every site profiled in the IAP study. To include the potential for expanding into slower wind-speed sites, I add an additional set of sites identical to the IAP sites, but with hourly power production that is uniformly reduced by 30 percent. This roughly corresponds to a rescaling from a Class 4 wind site (currently considered economically viable) to a Class 3 site. I also chose this scaling factor to ensure that the additional sites mostly have lower wind speeds than the sites in the IAP study, so that they represent the next tranche of sites available for development in the same geographic area. Figure 4 shows the gross distribution of wind speeds throughout the state of California, based on an earlier Truewind study (Brower 2002), as well as the areas and wind speeds used for the IAP study, and the sites used for the Switch model, after augmenting the IAP study.\textsuperscript{13} The IAP study used

\textsuperscript{13} Wind speeds for original and augmented IAP wind farms are estimated from capacity factors via the power curves shown in Figure 2. I assume that turbines are separated by 3 rotor diameters in one direction and 10 in the other, so that a class 1 or 2 site needs 11.9 ha/MW and a class 3 site needs 13.6 ha/MW.
about 10 percent of California’s wind sites with speeds of 7.5 m/s or more; the augmented sites make up about 5 percent of the locations with speeds of 6–7.5 m/s.

This approach implicitly assumes that these lower-wind sites have exactly the same timing as the previously studied sites; in reality, these sites may be in other parts of the state, and/or may have winds at different times than the IAP sites, yielding a more reliable aggregate portfolio than my assumptions indicate.

Figure 4. Potential land area for wind farms in California, and area available in IAP analysis and Switch model. Note: gross California potential is shown at 1/10 scale

4.9.1.3 Location of IAP Sites

The IAP provided minimal information on the location of the sites that they modeled. In the IAP dataset, each wind farm is assigned to one of the 14 focus areas shown in Figure 5, but no further information is available on the exact location.
For my work, I treated wind farms as if they were located at arbitrary points in the most deeply-colored region near the center of each resource area. Table 7 shows the resource areas identified by the IAP, the total high-speed capacity that the IAP study assumed would be installed in each area, and the total high- and low-speed capacity that I assume are available for development in the Switch model. In all, the Switch model is allowed to install wind turbines at 466 potential wind farm sites, with a total capacity of
up to 46,028 GW. Around 75 percent of this capacity is located in the “Other SCE” load zone.

Table 7. Wind farm locations and sizes

<table>
<thead>
<tr>
<th>Resource Area</th>
<th>IAP</th>
<th>Switch Model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ID</strong></td>
<td><strong>Name</strong></td>
<td><strong>Capacity (MW)</strong></td>
</tr>
<tr>
<td>1</td>
<td>Warner</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>Shasta</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>Montezuma</td>
<td>23</td>
</tr>
<tr>
<td>4</td>
<td>Solano</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>Altamont</td>
<td>26</td>
</tr>
<tr>
<td>6</td>
<td>Pacheco</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>Sequoia</td>
<td>4</td>
</tr>
<tr>
<td>8</td>
<td>Tehachapi</td>
<td>73</td>
</tr>
<tr>
<td>9</td>
<td>E_Mojave</td>
<td>34</td>
</tr>
<tr>
<td>10</td>
<td>W_Mojave</td>
<td>19</td>
</tr>
<tr>
<td>11</td>
<td>S_Gorgonio</td>
<td>28</td>
</tr>
<tr>
<td>12</td>
<td>Vallecita</td>
<td>1</td>
</tr>
<tr>
<td>13</td>
<td>Jacumba</td>
<td>4</td>
</tr>
<tr>
<td>14</td>
<td>Yuma</td>
<td>6</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>233</strong></td>
<td><strong>23,014</strong></td>
</tr>
</tbody>
</table>

4.9.2 Solar Resources

4.9.2.1 California Irrigation Management Information System

Hourly irradiances for solar troughs and photovoltaic systems are derived from a dataset of hourly horizontal global shortwave irradiance measurements, developed by the California Irrigation Management Information System (CIMIS). This program, operated by the California Department of Water Resources, collects a variety of meteorological data from a network of about 200 monitoring stations, for use in modeling evapotranspiration throughout the state of California (CIMIS 2006). I estimated hourly
capacity factors for solar troughs and photovoltaic systems based on hourly irradiance measurements for 117 stations that had collected data during at least 90% of the hours between November 2002 and October 2004. A small number of missing hours were filled in with the average of the previous and next hour.

4.9.2.2 Solar Thermal Trough Power Production

Solar thermal electric troughs are assumed to be installed at exactly the location of the CIMIS measurement systems. This is a conservative assumption, because there are likely to be good solar resources closer to load centers.

I first calculated the direct beam irradiance expected on a solar thermal trough each hour, based on the irradiance measured on a horizontal surface. I then calculated the capacity factor from this. The irradiance calculation is based Perez et al.’s anisotropic sky model (1987, 1988), cited in Duffie and Beckman (1991). This model first estimates a sky clarity parameter based on the measured horizontal flat-plate irradiance, latitude, longitude and solar angle. It then uses this parameter to calculate various components of radiation: direct beam, isotropic diffuse, circumsolar diffuse, diffuse from the horizon, and ground reflection. These components are illustrated in Figure 6.
To convert this hourly irradiance into an hourly capacity factor, I first assume that solar thermal troughs receive the amount of direct-beam radiation that would be incident on a one-axis, horizontal tracking surface, with a north-south axis, as calculated via the Perez model. I further assume that the capacity factor for these facilities would be 100% under 1000 W irradiance, and that it scales linearly with irradiance, and that these systems have no ability to store energy between hours.

4.9.2.3 Photovoltaic Power Output

I assume that solar photovoltaic systems can be installed anywhere in extended “solar zones” around each CIMIS station. These solar zones are defined as follows. I first assign each CIMIS station to one of CIMIS’s reference evapotranspiration zones, using GIS data provided by the CIMIS (CIMIS 1999). These zones are listed in Table 8. I next assume that all photovoltaic systems in the same evapotranspiration zone and within 200 km of each station have the same hourly solar conditions. The stations and their corresponding land areas are shown in Figure 7.
Table 8. California evapotranspiration zones

1. **Coastal Plains Heavy Fog Belt.** This zone has the lowest ETo in California and is characterized by dense fog.
2. **Coastal Mixed Fog Belt.** Higher ETo than zone 1 and less fog.
3. **Coastal Valleys and Plains and North Coast Mountains.** More sunlight than zone 2.
4. **South Coast Inland Plains and Mountains North of San Francisco.** More sunlight and higher summer ETo than zone 3.
5. **Northern Inland Valleys.** Valleys north of San Francisco.
6. **Upland Central Coast and Los Angeles Basin.** Higher elevation coastal areas.
7. **Northeastern Plains.**
8. **Inland San Francisco Bay Area.** Inland area near San Francisco with some marine influence.
9. **South Coast Marine to Desert Transition.** Inland area between marine and desert climates.
10. **North Central Plateau and Central Coast Range.** Cool, high elevation areas with strong summer sunlight. This zone has limited climate data and the zone selection is somewhat subjective.
11. **Central Sierra Nevada.** Sierra Nevada Mountain valleys east of Sacramento with some influence from the delta breeze in summer.
12. **East Side Sacramento-San Joaquin Valley.** Low winter and high summer ETo with slightly lower ETo than zone 14.
13. **Northern Sierra Nevada.** Northern Sierra Nevada mountain valleys with less marine influence than zone 11.
14. **Mid-Central Valley Southern Sierra Nevada, Tehachapi and High Desert Mountains.** High summer sunshine and wind in some locations.
15. **Northern and Southern San Joaquin Valley.** Slightly lower winter ETo due to fog and slightly higher summer ETo than zones 12 and 14.
16. **Westside San Joaquin Valley and Mountains East and West of Imperial Valley.**
17. **High Desert Valleys.** Valleys in the high desert near Nevada and Arizona.
18. **Imperial Valley, Death Valley and Palo Verde.** Low desert areas with high sunlight and considerable heat advection.
I then divide the solar zones where they are split among load zones, and estimate the population in each of these solar-load zone combinations, based on 2000 census data. I assume that the roof area in each of these solar-load zones is proportional to the population in that region, and that there is enough roof area to install 1 kW of solar panels per person.

4.9.2.3.1 Solar Panel Orientations

The Switch model is allowed to choose among three panel orientations in each solar zone. These face directly toward the sun at 12:30, 2:30 or 4:30 pm, on the vernal and autumnal equinoxes. Midpoints of each hour were chosen, in order to estimate the average production during a full hour period as closely as possible. I assume that one
twelfth of the available roof area faces in each of these directions (or close enough to treat as if it does).

The orientation of these panels is described by the slope, $\beta$, and the azimuth, $\gamma$ (the horizontal angle relative to due south). Solar panels face the sun when they are oriented in such a way that:

$$\beta = \theta_s \quad \text{(the solar zenith angle at a given time)} \quad \text{and} \quad \gamma = \gamma_s \quad \text{(the solar azimuth angle at a given time)}$$

The angles are illustrated in Figure 2 below.

![Diagram of solar panel angles](image)

*Figure 8. Angles used to find the optimal orientations for solar power production. Reproduced from Duffie and Beckman (1991)*

Finally, I use the same directional irradiance parameters as in section 4.9.2.2 to calculate the total irradiance on each tilted panel, during each hour.

### 4.9.2.3.2 PV Capacity Factor

The nameplate rating of photovoltaic systems usually indicates the amount of power it would produce under bright-sun conditions, corresponding to 1000 W/m² of radiation at standard atmospheric conditions. The power output from a solar module
also generally varies approximately proportionately with the radiation striking its surface. Using these facts, I developed a simple model for the capacity factor of solar PV installations during any hour as a function of the total radiation striking the surface of the panel:

\[
\text{capacity factor} = \frac{\text{power output}}{\text{rated power}} = \frac{\text{irradiance}}{1000 \text{W/m}^2}.
\]

### 4.10 Transmission Lines

The Switch model defines possible transmission corridors along straight-line paths between the centers of every pair of load zones. The cost of expanding power transfer capability along each corridor is assumed to be $1,000 per MW-km (in 2007 dollars). This is intended to include the cost of a new line linking these load centers, as well as any other costs needed to ensure that power can be transferred securely along the corridor (e.g., upgrades to nearby lines to avoid short-circuits, or upgrades to transformer banks). Costs for power lines alone have been cited elsewhere at $400–$600 per MW-km (Fuldner 1996; IPC 2007).

The existing transfer capability between each pair of load zones is calculated as the sum of the “capacity” of all high-voltage transmission lines connecting those load zones, as reported in the 2007 filing of FERC Form 715 by the Western Electricity Coordinating Council (WECC 2007). For these purposes, the “capacity” of each line is defined as the lesser of its thermal limit, or its limit as reported in the 2007 WECC path rating catalog (WECC 2007).\(^{14}\) Ratings in the WECC path rating catalog reflect the maximum power that can be transferred along that path, without overloading other lines.

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\(^{14}\) In cases where a single WECC path is composed of multiple transmission lines, I allocate the combined rating among the individual lines, proportional to their thermal limits. For paths with different limits in each direction, I assign corresponding directional limits to the individual lines that make up the path.
or creating instability if there is a sudden outage of a power line or plant anywhere in the system. These ratings are calculated by the WECC and transmission owners, using full power flow models under a variety of operating conditions. Although the Switch model does not endogenously model these non-linear constraints on the power system, it does respect all the ones that have been included in the path rating catalog.

For the work reported here, the Switch model is allowed to expand transfer capability along corridors where transmission lines already exist, or build new transmission along any other corridor that is shorter than 300 km. These routes are shown in Figure 9; routes with existing transmission capacity are highlighted in green. Routes longer than 300 km are excluded to prevent the unrealistic addition of small-capacity, long-distance transmission lines between non-adjacent load zones.

The power system designed by the Switch model will have a different arrangement of power sources and transmission lines than the current power system, which will change the nature of loop flows. Consequently, it is possible that its generation and transmission plan may overload some paths that have not been studied before, or will relieve some of the constraints that have already been identified in the path rating catalog. I assume for the purposes of this study that these effects will not radically change the cost of the power system one way or the other. It would be valuable to perform a detailed power-flow analysis of the investment plan proposed by the Switch model, to identify the specific network upgrades that are needed, both to provide the new transfer capability that it proposes, and to avoid overloading existing transmission lines.

Each transmission path is assumed to be 95 percent efficient at delivering power. This is broadly consistent with the losses reported for existing lines in the WECC FERC 715 filing (WECC 2007). It is assumed that the voltage and conductor diameter of new
lines are chosen to keep losses at this level or less, and that economies of scale for longer
transmission lines keep their costs per kilometer the same as shorter lines, while maintain-
ting the same level of losses.

![Figure 9. Existing (green) and potential (black) transmission routes in California](image)

4.11 **Local Transmission and Distribution Capacity**

The cost of delivering power within each load zone, from the transmission hub to
distributed loads, is parameterized by a single cost for “local transmission and distribution
capacity.” The model is required to build enough of this generic capacity within each load
zone to satisfy the peak load during each investment period. There is then a fixed annual
charge to maintain this capacity during each year from that time forward. This is similar
to the idea of a demand charge for large electricity customers, to cover the cost of transmission and generation infrastructure to meet their peak load.

The peak load each period is calculated net of any power generated by distributed PV systems, and net of any reduction in power consumption due to demand elasticity. Interruptible loads are not assumed to reduce the need for local transmission and distribution because they are unlikely to be called upon to relieve such local congestion.

For the work reported here, I use a cost of $100/kW/year for local transmission and distribution capacity. Little information is available on the cost of providing this service, but this value is in the range suggested by several sources:


(2) Ofgem (2003) reports that distribution costs make up 25–30 percent of British power bills. If they make up a similar proportion of California power bills, and California has a load factor of 0.6 and average power costs of $0.12/kWh, then this would mean that a customer with a 1 kW peak load would incur 0.6 kWa/kWp x 8760 hours/year x $0.12/kWah * 0.25 = $160/kWp/year in distribution costs.

(3) The Modesto Irrigation District assess a demand charge of $8.80/kW/month to large customers (MID 2008). That charge would equate to $106/kW/year, if all customers’ loads were coincident, and every month had the same peak load. The Modesto Irrigation District is approximately the same size as the load zones in the Switch model, and it may be fair to assume that they set this charge at a level
roughly equal to their costs for delivering power from the high-voltage grid to their customers.

### 4.12 Fuel Prices

Forecasts of California natural gas, uranium and coal prices for each future year are taken from the CEC's Cost of Generation Study (Klein and Rednam 2007), which in turn come from work done for the 2007 Integrated Energy Policy Report (CEC 2007a); prices for each investment period are shown in Table 9.

**Table 9. Forecast prices for natural gas, nuclear fuel and coal**

<table>
<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>2005(^{15})</td>
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<td>0.56</td>
<td>1.60</td>
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<tr>
<td>2010</td>
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<td>2014</td>
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<tr>
<td>2018</td>
<td>7.56</td>
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<tr>
<td>2022</td>
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<td>2038</td>
<td>11.06</td>
<td>2.20</td>
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</tr>
</tbody>
</table>

### 4.13 Projected Levelized Cost of Power

Figure 10 combines the information presented throughout this section, to show the levelized cost of power from generation plants of each type that can be added to the Switch model. Points on the left side of this figure show historical costs, and the curves on the right are the projected costs used by the Switch model. For the purposes of this

\(^{15}\) Prices in this data series were not available for 2005, so I used prices from 2006 for this year.
figure, combined cycle gas plants are assumed to run at a 47 percent capacity factor, wind farms have 34 percent capacity factor, solar thermal troughs have a 27 percent capacity factor, and photovoltaic systems have a 21 percent capacity factor. These are typical values for the systems used in the Switch model. Interconnect costs are also added as follows: $64/kW for CCGT plants, $330/kW for wind projects, and $250/kW for solar thermal troughs.

*Figure 10. Historical and projected levelized costs of electricity from various generation technologies*
Part II: Results

The Switch model can be used for a wide variety of “experiments” analyzing the relationship between marginal costs of emission reductions and the composition of the power system. Here, I report the results of several analyses. Chapter 5 discusses the optimal power system under “base case” assumptions of a $30/ton carbon dioxide cost. It also investigates the marginal cost and benefit of adding wind and solar sites, and identifies factors that are likely to limit their cost-effective development, under any particular carbon-cost regime. Chapter 6 considers how the optimal portfolio changes as assumptions about the cost of carbon dioxide emissions are changed. Chapter 7 investigates the sensitivity of the investment choices to assumptions about equipment costs, fuel costs and other important factors. Chapter 8 takes a tentative look at the potential for achieving very sharp emission reductions, in a scenario with high carbon dioxide costs, additional power storage, and reschedulable electricity loads.
CHAPTER 5: OPTIMAL SYSTEM DESIGN WITH BASE-CASE ASSUMPTIONS

In this chapter, I discuss the power system investments proposed by the Switch model for 2010–26, when a “base-case” cost of $30/tCO₂ is assigned to carbon dioxide emissions.

This cost is close to the level expected by the California Public Utilities Commission in coming years, and is also close to the “social cost” of greenhouse gas emissions estimated by several studies. I find that the lowest-cost power system under these conditions generates 28 percent or more of its power from wind, solar and geothermal resources by 2022. This suggests that California’s current requirement of 20 percent renewable power by 2020 may be too low, but the 33 percent RPS proposed by 2030 is roughly consistent with expected costs for carbon dioxide emissions.

Many previous studies have focused on the potential “firm” or “capacity” contribution of wind and solar power sources, implicitly suggesting that the power system may only be able to use them cost-effectively if they provide some firm power, or conversely, that they should only be used to the extent that they fall within the reserve margin. On the other hand, other studies suggest that intermittent renewable resources can provide more firm power if they are aggregated across many sites. However, even these studies implicitly assume that renewables are only useful to the extent that they provide firm capacity. I find that the optimal power system for California uses enough fossil generators for about 95 percent of its firm capacity obligations (for the peak load plus a reserve margin), and is able to meet about 5 percent of its firm capacity needs with wind and solar power. However, the system obtains only about 72 percent of its energy from conventional plants, and 28 percent from intermittent renewables. This suggests that it may be cost-effective to add intermittent renewables to the system to save fuel from existing
gas plants; there is no clear point where renewables stop producing firm power, but also, that is not the main criterion for choosing renewables.

In the following sections, I first discuss how this “base case” carbon cost was selected. I next discuss the investments in generation capacity of each type during each investment period, and then present the allocation of energy production among the various types of generator.

5.1 Base-Case Carbon Dioxide Cost

The choice of a “base-case” cost for carbon dioxide emissions carries significant political weight. Lower costs suggest a worldview that greenhouse gas emissions cause little harm, are easily curtailed, or may never be subject to serious restriction. Higher costs suggest that we care deeply about greenhouse gas emissions and intend to exert serious effort to reduce them. Unfortunately, the selection of a particular cost can also be rather arbitrary – there is no unambiguous indication of what the “right” cost should be. Nevertheless, it is useful for the purpose of analysis to choose a single, “base-case” cost, in order to make statements that are meaningful for policymakers, and to create a reference scenario to which other scenarios can be compared.

The California Public Utilities Commission (CPUC) has addressed the question of what is the appropriate cost to ascribe future greenhouse gas emissions as part of its rulemaking on long-term generator acquisitions (CPUC 2005). They note that, “While CO2 limitation and regulation is controversial and uncertain, there is a wide range of potential cost levels, and an assumption of zero future does not adequately reflect the potential risk. Rather, a value that reflects the full range of reasonably possible outcomes would be more responsible” (CPUC 2005: 29). The CPUC ultimately required investor-owned utilities to use an adder of $8-25 (nominal) per ton of carbon dioxide emissions
when making long-term procurement plans, to account for the risk of future regulations.\textsuperscript{16} The CPUC selected these values as a best-guess estimate of the cost of emission permits in future years, but made no statement suggesting that this is the socially optimal cost for these emissions, and did not commit itself to setting taxes or permit prices at this level in the future.

A number of studies have sought to estimate the social cost of carbon dioxide emissions – the cost of all human and environmental harm caused by each ton of carbon dioxide released to the atmosphere. In principle, a carbon dioxide tax set equal to this value would maximize social welfare; alternatively, a power system that is designed as if such a tax were in place will also maximize social welfare. Tol (2005) reviewed 28 recent studies of the social costs of greenhouse gas emissions, and found a quality-weighted average value of $33 per ton of carbon dioxide (2007 US$; originally reported as $86/tC in 1995 prices). The Stern Review of the economics of climate change reported potential carbon dioxide damage costs of $31/ton (2007 US$) if the world moves along a trajectory toward atmospheric carbon dioxide concentrations of 450 ppm, or $105/ton (2007 US$) along a higher, business-as-usual trajectory (Stern 2007: 344).

Based on these studies, I adopt a base-case cost for carbon dioxide of $30/tCO\textsubscript{2}. This is a useful reference point for discussion, but should not be seen as an upper limit. In

\begin{footnotesize}
\textsuperscript{16} It is somewhat unclear exactly what numerical adder the CPUC has chosen. In April 2005, CPUC Decision D0504024 stated that “The E3 report [on avoided costs due to energy efficiency improvements (E3 2004)] examines a range of carbon values from $5 to $69 per ton of CO\textsubscript{2} and uses $8 per ton as a levelized cost in its analysis, based on a trend of $5 per ton in the near term, $12.50 per ton by 2008, and higher values thereafter. Adopting the E3 forecast of CO\textsubscript{2} values as an adder in the avoided cost calculation and forecast reasonably reflects the cost to California of carbon emissions” (CPUC 2005: 29). The values mentioned in this decision match those reported in the text of the E3 report (E3 2004). However, spreadsheets published by E3 in connection with this report show different costs from these documents: $8/ton in 2004, rising by 5 percent per year until 2023 and then by $0.90/ton each year thereafter, e.g., to $9.72 in 2008, $12.41 in 2013 and $26.44 in 2030 (see http://www.ethree.com/cpuc_avoidedcosts.html). Most reports quote the values from these spreadsheets as official policy, although they are lower than the values mentioned in the CPUC decision.
\end{footnotesize}
particular, if the world fails to move toward a lower-emission trajectory, or if positive feedbacks or catastrophic events turn out to be more likely than previously estimated, the true social cost of greenhouse gas emissions could be much higher.

It should also be noted that in most of the results reported here, the carbon cost is assumed to affect only the balance among power sources, but not the total amount of electricity that is generated. This is a conservative assumption, which likely understates the emission reductions possible when a $30 marginal cost is assigned to carbon dioxide emissions. This approach is probably a good approximation of the emission reductions if a $30 “adder” is used for long-term planning within the electricity sector, but never applied as a cost for customers to pay; or, equivalently, if a $30 carbon tax is assessed on “dirty” power sources, but then rebated uniformly along with every kWh of electricity sold (clean or dirty). Under these policies, the carbon adder would have no direct effect on the price paid by consumers for each kWh of electricity, so that consumers would face only the cost of using more-expensive, cleaner technologies, but not the cost of greenhouse gas emissions themselves. With these policies, consumers would not reduce their consumption of electricity as much as they would with an across-the-economy carbon dioxide tax (which could be used, e.g., to offset income taxes).

5.2 Generator Capacity

In this section, I discuss the Switch model’s choice of generator technologies in 2010–25, when a cost of $30/ton is assigned to carbon dioxide emissions. I find that intermittent wind and solar facilities contribute relatively little toward the system’s firm capacity requirements. However, the Switch model nonetheless finds them cost-effective to build on a large scale.
Figure 11 shows the optimal generation portfolio developed by the Switch model, using a $30/ton cost for carbon dioxide. As existing coal and gas plants are retired and loads grow, the optimizer adds new natural gas capacity to keep the total supply of dispatchable resources roughly equal to the system peak load each period. About 5.7 gigawatts of wind turbines are added to the system in 2010, and this capacity is gradually expanded to nearly 35 GW by 2022. The model also adds 280 MW of distributed photovoltaics and about 2.0 GW of solar troughs in 2022. The wind farms contribute little or no firm capacity toward the system’s reserve margin requirements during the first three investment periods, but the combined wind and solar facilities contribute about 3.8 GW toward these requirements in 2022–25. This corresponds to about 10 percent of the nameplate rating of wind and solar systems during this period, or about 5 percent of the system’s firm power requirements.

Figure 11. Generator capacity by type, 2015–26, $30/tCO2 carbon cost

The system builds more CCGT capacity than it needs to meet the reserve margin requirements during the first two investment periods. This may reflect a strategy of using new CCGT plants to save energy costs, even though their firm capacity is not needed.
It is interesting to note that the model builds substantial amounts of renewable resources by the end of the study period, even though they contribute relatively little toward the system’s firm capacity requirements. This suggests that the savings in fuel and carbon costs may be enough to justify investments in renewable resources, even if large amounts of conventional capacity are also built to maintain reliability. The Switch model’s early investments in wind power reflect the fact that over most of the course of the study the total, levelized cost of power from good wind sites (around $61/MWh in 2011 and falling thereafter) is projected to be lower than the variable cost of natural gas plants (gas and carbon dioxide emissions, totaling $63/MWh in 2011, and then rising). Marginal sites also gradually become cost-effective in later years.

By 2022, the optimal portfolio also includes a small amount of distributed photovoltaics, which can reduce the need for intrazonal transmission and distribution upgrades. Although solar thermal troughs would be able to provide some firm capacity, they are too expensive to include in the optimal portfolio in this particular model run.

### 5.3 Energy Supply

The previous section noted that wind generators provide little firm capacity, but the optimal portfolio nonetheless contains large investments in them. In this section, I show that these systems nevertheless make a significant energy contribution. This suggests that the best way to use large amounts of renewable resources is in combination with conventional plants; there is no need for them to displace conventional plants completely from the grid. Put another way, it appears to be cost-effective to develop renewable resources for their fuel- and carbon-saving benefits, even if they provide relatively little firm capacity.
Figure 12 shows the average production of power from each type of generator during each investment period. Nuclear, coal, gas and geothermal resources are used in a baseload mode, and provide a larger share of the system’s power than their nameplate capacity would suggest. Although many existing gas plants remain available, their energy contribution is largely supplanted by new CCGT plants. Power generation from wind sites grows over time, satisfying the increasing demand for electricity and beginning to displace coal plants and older gas plants. The share of power from wind and solar sources rises to 25 percent by 2022, and when existing geothermal plants are included this yields 28 percent of power from RPS-qualified renewables by 2022. This is a little below the 33 percent RPS recently proposed for 2020. Overall, the system obtains a total of 44–55 percent of its power from non-carbon resources (wind, solar, geothermal, nuclear and hydro) in each study period. It should also be noted that the renewable energy share would likely be higher if a more comprehensive set of wind sites were considered.

*Figure 12. Average power production, by source, 2010–25*
This suggests that it is cost-effective to obtain a significant share of energy from intermittent, renewable power sources, even if they must be partially backed up by fossil power plants elsewhere in the system. This finding contradicts the intuition implied in many RPS deliberations, that renewables can only be used up to an amount roughly equal to the system’s reserve margin, because at that point they will certainly not be able to reduce the need for gas capacity (because they are non-firm), so they will not be cost-effective. In contrast, I find that (a) renewables do provide some firm capacity (about 10 percent of the system’s firm obligation for peak load and reserve margin in this particular scenario), and (b) they are worth developing even if their firm capacity contribution is less than their energy contribution.

Rather than envisioning a system where intermittent generators are only used up to the point where they exhaust the reserve margin and/or stop displacing conventional generators from the grid, it may make more sense to consider a system in which conventional generators work mostly in backup mode, and renewable plants run whenever possible, even if this means idling conventional plants more of the time than we do now. Renewable resources may have a limited role to play as capacity providers, but they could nonetheless play an important role as pure fuel-savers. I discuss these findings in more detail in section 7.1.

5.4 Hourly Dispatch

This section explores the hour-by-hour decisions made by the Switch model, switching among intermittent and conventional resources. This shows that wind and solar power are often but not always available when loads are high. There are also some hours when all or nearly all of the load is carried by intermittent sources; this suggests that there will be new challenges to overcome in integrating optimal amounts of renew-
able power into the grid. It also sets the stage for the discussion of the surplus power problem in section 7.1.

Figure 13 shows the times of day and year when renewable and conventional resources are used on the peak load days, during the 2022–25 investment period. Figure 14 shows similar information for the randomly selected, “typical” day of each month. Each figure shows hourly statewide production by each type of generator, for one day each month. Baseload plants (coal, nuclear and cogen) are used in all hours, and wind and solar power are used when they are available. The optimizer has chosen somewhat west-facing photovoltaic orientations that produce more power later in the afternoon (these are barely visible in the figures below). Wind farms peak in the springtime and on summer nights. When combined, wind and solar resources yield ample power on “typical” days in February, March and April, and also have pronounced peaks on summer evenings. The model uses hydro and new CCGT plants to meet the remaining loads. Existing natural gas power plants are mostly used to serve peak loads for the whole system or in individual load pockets.
These figures indicate that California’s wind and solar resources are often available at times when power demands are high. However, there are some high-load hours
(e.g., the September peak) when little wind or solar power are available (at least at the sites chosen for development in this scenario); this likely explains why the model also includes enough gas power to serve the peak load and provide some reserve margin.

It is interesting to note that during late-night hours on the random days in March and April, electricity loads are low while wind power production is high, so that the intermittent power supply is nearly equal to the system load. In addition, April loads in all hours are fully satisfied by baseload, renewable and hydro resources. If investments in renewables were scaled up beyond the level shown here, it is easy to imagine that they would produce unneeded power during many springtime days. This points to two potential concerns. First, as renewable resources are added to the power system, some provision will need to be made for deactivating them or increasing loads during some hours, to avoid feeding excess power into the grid. Second, any power that is discarded will have no economic value. Consequently, beyond a certain point, the cost of renewable power plants will need to be justified based on the power they produce in other times. As investments in renewable generators are increased further, there will be more such hours, and the marginal benefits of renewable generators will steadily drop. In section 7.1, I discuss the possibility that this generation of surplus power may be the ultimate limit to the cost-effective use of renewable power, at any carbon-cost level.

5.5 Geographic Arrangement of Power System Investments

In this section, I present the geographic distribution of power generation and transmission investments chosen by the Switch model. By 2022, the optimal portfolio contains large amounts of low-cost wind power in the SCE service territory (mostly in Tehachapi), as well as some new wind power in northern California, and substantial amounts of CCGT capacity in the Bay Area. However, the state does not appear to need
large amounts of additional long-distance transmission capacity to take advantage of these resources.

Figure 15. Transmission capacity and average power production, by source and location, 2022–25, with $30/tCO₂ carbon cost

Figure 15 shows the geographic arrangement of transmission capacity and power production in 2022–25 in the base-case scenario. Pie charts show the amount and type of power generated in each load zone during this period. The Switch model installs and uses new CCGT natural gas plants in most load zones, and generates substantial amounts of wind power in the Other SCE, San Diego and PG&E North zones. A small number of solar photovoltaic systems are built in Los Angeles (but nowhere else), and new solar troughs are installed along a central-California corridor stretching northward from San
Diego and the Imperial Valley, through the Other SCE and PG&E South zones. With these additions, the Other SCE zone emerges as a major supplier of electricity for the state. (These findings would likely differ if more wind locations were considered than those reported in the Intermittency Analysis Project; the optimal power portfolio includes nearly all available wind resources, which in this study are artificially concentrated in the “Other SCE” load zone.)

Each existing transmission corridor is shown in Figure 15 as a wide green line; I cannot show the exact value of existing transfer capabilities, because I obtained these data under a non-disclosure agreement. Transmission additions are shown as darker blue lines, with a width roughly indicating the amount of capacity added during the study. Dotted blue lines indicate corridors where the model could have installed additional transfer capability but did not. The model adds no transfer capability along existing corridors, but does add small amounts of new transmission between the Geysers and San Francisco zones, and between Geysers and Sacramento. In all, it adds about 300 MW of interzonal transmission capacity, which is much less than the approximately 96,000 MW of existing transfer capability. This suggests that, at least up to 28 percent renewables, the most cost-effective option for California is to continue relying mostly on its existing long-distance transmission capacity.
In this chapter, I use the Switch model to investigate how the optimal investment strategy for the power system changes as the cost assigned to carbon dioxide emissions varies. I explore this question from three perspectives, each of which is relevant for different types of policymaking.

First, I show the optimal investment strategy for each possible carbon dioxide cost between $0/tCO₂ and $200/tCO₂. This analysis is useful for identifying the threshold costs at which individual generation technologies become economically viable or unviable. It could also be used to identify the optimal formulation of a renewable portfolio standard, if one has a particular view of the social cost of carbon dioxide emissions.

Second, I show the greenhouse gas emission reductions that can be achieved in the power system at each carbon cost level. This information constitutes a “supply curve” for emission reductions from the electricity sector, and is one of the most useful outputs from the Switch model. It can be used to for a variety of policy analyses. For example, if one is considering a statewide carbon dioxide tax at a specific dollar level, this curve will indicate the amount of emission reductions that can be achieved in the electricity sector in response to the tax. Or the supply curve for the electricity sector can be combined with similar curves for other sectors of the economy, to develop a California-wide supply curve for greenhouse gas emission reductions. This combined curve can then be used to find the carbon dioxide tax that would be needed to achieve any particular level of statewide emission reductions, or the likely price of tradeable emission permits if a cap-and-trade system is set at any particular statewide emission level. It is also possible to use this curve to identify the socially optimal emission reductions for individual sectors, to meet any particular statewide target. (First, choose a statewide target; next, read the marginal
carbon cost corresponding to that target from the statewide emission reductions curve; finally, use the emission reduction supply curves for each individual sector (e.g., the supply curve for the electricity sector developed here) to find the emission reduction for that sector corresponding to this statewide carbon cost.)

Third, I show how the average cost of California electricity increases as greenhouse gas emissions from the electricity sector are reduced. This information can be used in assessing the political feasibility of adopting any particular greenhouse gas emission reduction target. I find that the effect on power bills is relatively modest, even with sharp reductions in greenhouse gas emissions.

6.1 Composition of the Power System

In this section, I show how the optimal mix of generation technologies changes as the cost of carbon varies between $0/tCO\text{2} and $200/tCO\text{2}. I conclude with a brief discussion of the policy implications of the findings shown here.

Figure 16 shows the composition of the optimal power system (as of the final investment period), when carbon dioxide costs are varied from $0 to $200 per ton. When no cost is assigned to carbon dioxide emissions, the optimal power system includes about 25 GW of wind farms, and this rises to a level of 35 GW for carbon costs of $30/tCO\text{2} or higher, then slowly rises from there, up to 42 GW (out of maximum possible capacity of 46 GW) for carbon costs of $200/tCO\text{2}. Coal plants in the Southwest become uneconomic when carbon costs exceed $50, but it is cost-effective to keep other existing plants online at all carbon prices. The model steadily increases investments in solar thermal troughs as the carbon dioxide cost rises above $30/tCO\text{2}$, reaching 35 GW at $200/tCO\text{2}$. For each gigawatt of solar that the model adds up to 22 GW (at a $150/tCO\text{2}$ carbon cost), it reduces its investment in natural gas capacity by about 0.4
GW. Beyond this point, the model continues adding solar capacity, but no longer reduces its investment in new natural gas capacity. This suggests that at higher carbon costs, the model uses solar troughs in a “fuel-saving” mode, to reduce the cost of fuel and carbon dioxide emissions, even if additional solar facilities do not reduce the need for natural gas plants during peak hours.

Figure 16. Installed capacity of each type, 2022–25, with carbon costs of $0–200/tCO₂
Figure 17. Share of power production from each source, 2022–25, with carbon costs of $0–200/tCO₂

Figure 17 shows the share of electric power that comes from each type of generator in the optimized portfolio, for the same time period and carbon costs. In keeping with the previous graph of generating capacity, coal power production is phased out at costs above $50/tCO₂, and the share of power coming from other existing plants or new wind plants varies little in response to the carbon cost. However, the optimal portfolio switches steadily from natural gas to solar troughs as the carbon dioxide cost rises from $30/tCO₂ to $200/tCO₂. The share of power supplied by RPS-qualified resources (geothermal, wind and solar) rises smoothly from 21 percent with no carbon cost, up to 52 percent with a $200/tCO₂ cost. The share of power coming from all non-carbon sources (including nuclear and hydro) varies smoothly between 48 percent and 78 percent.

These findings have three immediate policy implications: First, the Switch model suggests that a 20 percent RPS for the 2020 time frame is probably too low. Even if no
cost is assigned to carbon dioxide emissions, the least expensive option for the state will be to obtain 21 percent of its power from renewable resources by 2024. Second, the proposed RPS target of 33 percent by 2020 would be consistent with a social cost of carbon around $60/tCO₂ (this may be lower if less conservative assumptions are used, such as considering more wind sites). Third, there appears to be no sharp limit to the amount of renewable power that the system can use, at least up to a carbon cost of $200/tCO₂. The only limit to emission reductions from the power system is the state’s willingness to pay to achieve these reductions.

6.2 Emission Reduction Supply Curve

In this section, I turn my attention to the relationship between the marginal cost of carbon dioxide emissions, and the amount of emission reductions that can be achieved in the electric power system. I first introduce the “supply curve” approach that has been used increasingly to analyze climate change mitigation options in recent years. I then present a supply curve for emission reductions in the California power system, developed using the Switch model. Finally, I discuss how this curve can play an integral role in formulating an efficient greenhouse gas emission reduction strategy for California.

6.2.1 Introduction to Emission Reduction Supply Curves

Economic analyses of climate change have increasingly relied on “supply curves” of greenhouse gas emission reductions. Figure 18 (Fitch 2008) shows a relatively simple example of an emission reduction supply curve for the electricity sector. The authors first identified a range of activities that could be undertaken to reduce emissions, and calculated the cost of each of these activities per ton of emission reduction. For example, they estimated that utilities could use biogas to generate electricity, saving greenhouse gas emissions at an incremental cost of $70/tCO₂. They then sorted these activities from
least expensive to most expensive, and plotted them on a graph. On this graph, the x-axis shows the cumulative emission reductions (beginning with the least expensive activity), and the y-axis shows the cost per ton of emission reductions for each activity. This curve then traces out the marginal cost of achieving various levels of emission reduction, or conversely, the total amount of emission reductions that can be achieved at or below any particular marginal cost. For example Figure 18 indicates that about 15 million tons of CO₂-equivalent can be eliminated at a cost of about $160/tCO₂ or less, and that these reductions would best be achieved by investing in all the options to the left of the 15 MMT mark (i.e., on-site combined heat-and-power through wind farm development).

![Figure 18. Emission reductions possible from California light-duty vehicles in 2025, without hybrids or alternative fuels. Reproduced from Fitch (2008)](image_url)

Since they clearly show the relationship between emission reduction quantities and marginal costs, emission reduction supply curves can a valuable tool in setting efficient emission reduction policies. For example, if it were known that each ton of carbon dioxide emitted into the atmosphere would cause $150 of damage, then Figure 18 sug-
gests that California should invest in all the activities up to and including the California Solar Initiative (CSI), since they can each achieve emission reductions at a lower cost than this (i.e., the cost of each of them is less than their benefits, in terms of avoided environmental harm). Furthermore, it suggests that this optimal emission reduction strategy would eliminate about 12 million tons of CO₂, relative to the authors’ baseline.

6.2.2 Using the Switch Model to Develop an Emission Reduction Supply Curve for the California Power System

An emission reduction supply curve can also be built using the Switch model. This is done by running the model repeatedly with different marginal costs for carbon dioxide emissions, and then plotting the total emission reductions that can be achieved in response to each carbon cost.

This technique works because when the Switch model develops an optimal investment portfolio based on any given carbon cost, it implicitly makes all investments that can reduce carbon dioxide emissions at a cost at or below this target. For example, if the Switch model is run with a carbon cost of $50/tCO₂, it will develop renewable energy facilities up to exactly the point where additional emission reductions would cost more than $50/tCO₂. If adding more renewable energy could reduce emissions at a lower cost than this, the optimizer would do so, since this would reduce the total cost of energy plus carbon dioxide emissions. On the other hand, the optimizer will go no further than this point, because doing so would mean spending more on renewable energy than the emission reductions were worth. So it is possible to make a supply curve for emission reductions by running the Switch model repeatedly with different carbon costs, and plotting the total emission reductions achieved up to that carbon cost.
Figure 19 shows an emission reduction supply curve developed in this manner. Here, for each carbon dioxide cost from $0 to $200/tCO₂, I have plotted the emission reductions that can be achieved in the electricity system, relative to the 1990 level. These reductions are shown in millions of tons of carbon dioxide on the lower axis, and in percentage terms on the upper axis. I use 1990 emissions as the baseline, because California’s AB32 legislation commits the state to specific targets relative to this level.

The electricity sector released 87 million tons of CO₂ in 1990, both in-state and to generate power imported to the state. In every case, the lowest-cost power system proposed by the Switch model includes large amounts of wind power and replaces older fossil plants with newer, more efficient CCGT gas plants. Consequently, even with no carbon cost, the lowest-cost system emits only 75 million tons of CO₂, a reduction of about 12 million tons relative to the 1990 baseline. Emission savings increase from that level as the cost of carbon dioxide is raised, up to about 44 million tons if carbon dioxide emission reductions are valued at $200/ton. These correspond to reductions of 14–65 percent from the 1990 levels.
My work with the Switch model (Figure 19) suggests that greater emission reductions are possible at lower costs than the supply curve shown in Fitch (2008) (Figure 18). This is chiefly because the E3 study reported by Fitch uses current equipment costs instead of declining forecasts, and uses higher interest rates than I do.

It should also be emphasized that the supply curve shown here is not the last word on emission reductions from the electricity sector. This curve is based on fairly conservative assumptions, and should be seen as the lower limit for the supply of reductions. This curve could be pushed further to the right by faster reductions in renewable energy costs, use of additional wind sites that weren’t included in this study, development of pumped hydro or other storage systems, more flexible use of the existing hydro system, improved efficiency in the use of electricity, conservation of electricity, or shifting loads from times when renewable power is scarce to times when it is abundant. On the other hand, the outlook could be worse, if solar troughs don’t achieve the cost reductions that have been
projected, the cost of wind farms stops declining at its historical rate, natural gas prices fall, or policies are unable to precisely promote the most cost-effective operation of the power system. I assess the potential effect of several of these factors in Chapter 8.

6.2.3 Policy Implications

The emission reduction supply curve for the electricity sector can be used in two ways: to assess the effect of environmental policies within the electricity sector, or to help develop an efficient, economy-wide emission reduction strategy.

6.2.3.1 Assessing Emission Reduction Options in the Electricity Sector

The emission reduction supply curve shown in Figure 19 clarifies a relationship that has not previously been well quantified, between the marginal cost of reducing greenhouse gas emissions, and the amount of emission reductions that are possible in the power sector. This information can be used to help develop efficient policies for reducing greenhouse gas emissions from the electric power system.

For example, suppose that policymakers estimate that greenhouse gases cause $50 worth of harm per ton of CO₂ emitted, and they want to use this information to decide how many carbon dioxide emission permits to issue in a cap-and-trade system in the electricity sector. They can refer to the supply curve to find that about 29 MtCO₂ could be eliminated from the electricity sector for a cost below $50, which indicates that the socially optimal number of carbon dioxide permits is 29 MtCO₂ below 1990 emission levels.

Conversely, if policymakers wish to reduce electricity-sector emissions by 60 percent below 1990 levels, Figure 19 can be used to determine that a carbon tax around $120/tCO₂ could achieve this objective. Equivalently, if a cap-and-trade system is used,
with a cap set at 60 percent below 1990 levels, we can estimate that permits should end up selling for around $120/tCO₂.

6.2.3.2 Developing Efficient, Economy-Wide Emission Reduction Strategies

The brief policy discussion in the previous section focused on decisions about emission reductions in the electricity sector alone. However, greenhouse gases are emitted by a wide variety of activities in California, in addition to electricity production. In this section, I discuss how the electricity-sector emission reduction supply curve can be used as part of a process to set optimal emission reduction targets for all sectors of the economy.

In principle, the most direct way to achieve an optimal level of emission reductions in each sector of the economy would be to adopt a statewide tax on greenhouse gas emissions, set at a level equal to the marginal value of harm done by each ton of greenhouse gas emissions.¹⁸ With such a tax, people engaging in any economic activity would pay a surcharge equal to the amount of damage done by their greenhouse gas emissions. Consequently, they would avoid all emissions that could be avoided for a cost less than the carbon dioxide tax, and continue activities for which the cost of reducing emissions is higher than the benefits.

Alternatively, rather than estimating the value of reducing greenhouse gas emissions, the state may find it easier to set a target for a “safe” level of greenhouse gas emissions to achieve. The state could then auction off exactly enough greenhouse gas emission permits to reach this target, under a cap-and-trade system.

¹⁸ There are substantial difficulties in estimating what this cost should be. However, it should be possible for the state to at least develop a single estimate of how much it is willing to pay for each ton of emission reductions, even if this price does not exactly equal the harm done.
Each of these statewide approaches faces a couple of political problems. First, they both have the same effect – adding a surcharge to activities that produce greenhouse gas emissions, and transferring the proceeds from that surcharge to the state. This large, new charge, imposed on a wide variety of economic activities, is likely to be politically unpopular. There may instead be a preference for policies that are revenue-neutral within individual sectors, such as separate cap-and-trade systems applied to the electricity and transportation systems, with permits granted directly to emitters in each sector, rather than being auctioned on a multi-sector basis. Another problem with these statewide, economic approaches is that they may not be as effective in some cases as more direct policies tailored to particular industries; for example, a carbon dioxide tax applied to gasoline may have less effect on consumers’ purchases of high-efficiency vehicles than a carbon-emissions standard applied directly to the vehicles offered for sale in the state.19

Both of these factors suggest that greenhouse gas emission targets may be set on a sector-by-sector basis, rather than using a full-economy carbon dioxide tax or cap-and-trade system. In this case, statewide emission reduction goals can be achieved most cost-effectively if targets for each sector of the economy are harmonized, so that roughly the same marginal cost of emission reduction is found in every sector of the economy. For example, if emission reduction targets are set too tightly in the electricity sector and too loosely in the transport sector, we could find that emissions are being reduced at a cost of $100/tCO₂ in the electricity sector, and only $30/tCO₂ in the transport sector. In this case, the electricity sector target should be loosened while the transport sector target is

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19 This differential arises in part because consumers sometimes exhibit a strong preference for low first-costs in their purchases, even if it means incurring high costs later. These preferences are out of line with other choices about the time value of money, such as selection of loans based on their interest rates. It also arises because auto manufacturers are more likely to invest in efficiency innovations – bringing down costs and raising public acceptance – if they are required to do so in order to make sales on a large scale in the state.
tightened – each ton of CO₂ restriction transferred from the electricity sector to the transport sector will save $100 in expenses in the electricity sector and increase costs by only $30 in the transport sector. This should be continued until marginal costs are equal in all sectors.

The simplest way to set these harmonized targets is by using emission reduction supply curves for each sector, including the one presented here for the electricity sector. This process can proceed in two ways.

First, if the state adopts a common estimate of the value of avoiding greenhouse gas emissions, then it will be a fairly trivial task to identify the optimal greenhouse gas emission target for each sector. One need simply refer to the emission reduction supply curve for each sector, and read off the emission level corresponding to the value of avoiding emissions.

If the state does not calculate the dollar value of avoiding greenhouse gas emissions, but instead adopts a target emission level (in tons of CO₂-equivalent) for the whole economy, then the process of setting efficient targets for each sector is somewhat more complicated. In this case, one would first need to choose a single dollar value for emission reductions, that, when applied to all sectors, yields the desired statewide emission reduction. For example, Figure 20 shows an emission reduction supply curve for California’s transport sector (Subin 2008). By referring to this curve and the emission supply curve for the electricity sector (Figure 19), we can see that the state can achieve emission reductions of about 17 million tCO₂ in the transport sector and 33 million tCO₂ in the electricity sector for a marginal cost equal to or below $35/tCO₂. So, if the state wants to achieve emission reductions of 50 million tons of CO₂, from these two
sectors, then the most efficient targets would be 17 million tCO₂ in the transport sector and 33 million tons of CO₂ in the electricity sector.

![Graph](image_url)

*Figure 20. Emission reductions possible from California light-duty vehicles in 2025, relative to a 1990 baseline, without hybrids or alternative fuels. From Subin (2008)*

If emission targets must be assigned to many separate sectors, then the process can be simplified by first combining the emission reduction supply curves from the individual sectors into a single, economy-wide supply curve. This technique is used by Vattenfall AB for their climate impact abatement roadmap (Josefsson 2007) (Figure 21). If a curve like this were developed for California, the marginal cost of achieving any economy-wide emission target could be read directly from the master supply curve. This cost could then be used with the supply curves for individual sectors, to identify the optimal emission target for each sector, or to identify the optimal set of emission reduction activities to undertake in each sector.²⁰

²⁰ Many studies indicate that the marginal harm done by each ton of carbon dioxide emissions increases as the cumulative emissions level increases. So the supply-and-demand analog can be completed by drawing a downward-sloping “demand curve” showing the diminishing value of emission reductions (avoided damage) as emission reductions increase. The point where these two curves intersect would be the optimal regional or global emission reduction target.
This supply-curve approach is likely to be important in California, as most recent climate change policy measures (e.g., AB32 and the RPS) use emission reduction targets rather than marginal damage values. Consequently, a supply curve like the one generated by the Switch model may be an essential tool in setting emission targets for the electricity sector and other parts of the economy.

Before closing this section, I should note that even with harmonized targets, a sector-by-sector approach may not be as economically efficient as a statewide carbon tax or cap-and-trade system. As noted above, one of the key reasons to use separate targets for each sector is to avoid adopting policies that transfer funds out of that sector to the state. However, if revenue-neutral targets are set within each sector, then consumers of products from each sector may not face the full cost of the damage caused by production in that sector. For example, if a carbon “adder” is used in electricity investment and dis-
patch decisions, but not actually added to the price of electricity, then consumers will not factor the full environmental cost of greenhouse gas emissions into their decisions about how much electricity to use. Consequently, they will purchase more electricity than they would if they had to account for the environmental externalities. Put another way, revenue-neutral strategies within each sector could ensure that goods are produced in an environmentally-optimal way, but may not ensure that the environmentally optimal amount of those goods is produced. The only way to reduce the consumption of goods to an environmentally optimal level is to incorporate the full cost of environmental impacts into the cost of each product. This can only be done with a policy that is not revenue neutral within individual economic sectors, such as a statewide carbon-tax or cap-and-trade system.

For the analysis reported so far, I have run the Switch model with no opportunities for demand reductions in response to more expensive power production or a carbon tax passed along to consumers. This means that its supply curve is more consistent with a sector-by-sector revenue-neutral emission control strategy than a statewide strategy. However, this analysis may also understate the emission reductions that would be achieved even with revenue-neutral electricity strategies, because electricity customers are likely to reduce consumption somewhat in response to the higher power bills associated with cleaner energy. I discuss the expected change in the cost of power in the next section, neglecting the cost of carbon or the effect on demand. Later, in section 8.4, I investigate how demand elasticity could affect the potential for emission reductions from the electricity sector, if customers face the full cost of cleaner electricity and a carbon tax.
6.3 Cost of Electricity

Policymakers and electricity customers are often more interested in the effect of climate change policy on the cost of electricity, than they are in abstract concepts such as the marginal cost of emission reduction. In this section I show how the average cost of electricity changes as the system is pushed toward lower greenhouse gas emissions. I find that reducing emissions could have a surprisingly modest effect on consumers’ power bills. This may make strong emission reductions politically palatable.

Figure 22 shows the average cost per MWh of electricity delivered in 2022–25, for optimal power systems proposed by the Switch model, with emission reductions ranging from 14 percent to 65 percent below 1990 levels. I prepared this figure by stepping the carbon dioxide cost from $0/tCO₂ to $200/tCO₂, and recording the emission reductions and the average cost of electricity for the optimal power system at each step. This shows the lowest cost that can be paid for electricity while achieving each level of emission reductions.²¹

²¹ At each step, if the model could obtain electricity at a lower price without increasing emissions, it would have done so.
The lower line in Figure 22 shows the average cost of generating power, net of any carbon dioxide cost. This is the average cost that would be paid by customers if the cost of carbon dioxide emissions is treated in a revenue-neutral way within the electricity system. The upper line shows the average cost per MWh, if revenues from a carbon tax or permit system are transferred out of the electricity system. This would be the case, for example, if proceeds from a carbon tax or cap-and-trade system were used to reduce statewide income taxes.

Even if California’s carbon dioxide regulations are not revenue-neutral within the electricity sector, it is probably most appropriate to make policy decisions on the basis of the costs shown in the lower plot line (the revenue-neutral case), because the difference between the two (i.e., the cost of the carbon tax or permits themselves) would be re-

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22 This could be done by taxing each carbon-emitting source and then rebating the proceeds to customers, or by providing tradeable emission permits to power producers at no cost. An alternative form of revenue neutral carbon “cost” would be if investment and operation decisions are optimized on the basis of analytical “adders” for the cost of carbon dioxide emissions, but no direct carbon tax is assessed.
turned to the population in the form of savings on other taxes. That is, the lower plot line includes all the direct costs associated with developing a lower-carbon power system (e.g., paying for more expensive generators), and excludes only the carbon dioxide tax, which might be a wealth transfer from one segment of society to another, but would not be a true cost.

The direct cost of generating electricity varies smoothly from $80/MWh with a 14 percent emission reduction from the 1990 baseline, up to $94/MWh with a 65 percent emission reduction (these reductions correspond to marginal carbon dioxide costs of $0 and $200, respectively). There does not appear to be a sharp upturn in costs at any point. These variations in cost are surprisingly modest – a $100/tCO₂ cost could reduce carbon dioxide emissions from the electricity sector by 51 percent compared to 1990, but would only increase the average cost of electricity by $6.90/MWh compared to the no-carbon-cost case. This is equivalent to about $3.45/month for a residential customer using 500 kWh/month.
CHAPTER 7: KEY FACTORS GOVERNING THE OPTIMAL LEVEL OF RENEWABLE ENERGY DEVELOPMENT

In this chapter I discuss some of the key factors that govern how much intermittent renewable energy can be developed cost-effectively in the power system.

I first use the Switch model to assess how the economic benefits of renewable power change as the power system uses more or less than the optimal amount. I find that the most fundamental limit is that if renewable resources are developed on a very large scale without any storage or demand-side flexibility, they will eventually begin to generate more power than is needed during some hours of the year. This power cannot be sold, and consequently reduces the value of the renewable power system. This “surplus power” problem is likely to be a more difficult limit than the problem of having too little firm capacity during peak load hours (which, as noted above, can be solved simply by building gas plants in addition to the renewable generators). This suggests that if we want to reduce greenhouse gas emissions from the power system as much as possible, it may be important to identify storage systems or reschedulable loads that can make use of this surplus power.

I follow this with a discussion of how the optimal investment portfolio would differ if California were able to use only wind resources, or only solar resources, instead of the combination of the two that I have assumed previously. This helps to reveal whether there are benefits to be gained by combining different renewable technologies (I conclude that there are).

For this chapter and the next, I have run the Switch model with a smaller number of sampled hours than in previous chapters, in order to produce results more quickly. For the rest of the studies in this thesis, I ran the model using only even-numbered hours,
during even-numbered months. In previous chapters, I used samples for both even- and odd-numbered months and hours. (In both cases, I have modeled one peak day and one random day each month.) Figure 23 shows the carbon supply curves developed using these two different versions of the model, and Figure 24 shows the relationship between emission reductions and the cost of electricity. The reduced-sampling version of the model produces an emission reduction supply curve that has the same general shape as the fuller version, but suggests emission reductions that are up to 7–15 percentage points below those found with the full model, at various carbon costs. The simplified model also estimates power costs about $5/MWh lower than the full model when achieving emission reductions around 30-70 percent below 1990 levels. This greater degree of optimism in the reduced model appears to be due to selection of months when wind and solar power are better matched to loads than they are in the fuller model.

Although the simplified model appears to be less accurate at estimating the exact composition of the optimal investment portfolio, it is nevertheless useful for elucidating how the optimal portfolio changes as assumptions are varied.

*Figure 23. Emission reduction supply curve derived from full model and model with reduced sampling*
Figure 24. Average cost of electricity in 2022–26, based on full model and model with reduced sampling

7.1 Marginal Costs and Benefits of Renewable Generators

My dissertation research frames the choice of how much wind and solar power to develop in economic terms: the Switch model develops wind and solar power if and only if their costs are lower than their benefits to the power system. In this section, I show how the benefits of intermittent renewable generators decrease as they are developed on a larger scale. I find that with any particular set of cost assumptions, there are two major categories of economic benefit from intermittent renewable power generators: capacity benefits (in the form of savings from conventional plants that don’t have to be built) and energy benefits (savings from avoiding the use of fuel and emission of carbon dioxide). Each of these benefits diminish as renewable energy is developed on a larger scale, and when they fall below the cost of renewable power plants, it inevitably becomes uneconomical to develop additional wind or solar sites.

In this section, I show that this process goes through two major phases: diminishing capacity benefits, which limit the deployment of relatively high-cost renewable energy equipment; and diminishing energy benefits, which place a more fundamental limit
on the deployment of renewable power systems, even if they are highly cost-competitive with conventional options. This suggests that in the long run, large-scale development of renewable power may be limited not by its inability to produce power during times of peak demand, but rather by the production of too much power during off-peak times. In turn, this suggests that it may be more important to focus policy efforts on activities and technologies that can make better use of off-peak electricity, rather than easing peak-hour constraints.

Wind and solar generators can provide two benefits to the system: contributions in capacity to serve peak loads (reducing the need for other power plants), and contributions toward the system’s energy needs (reducing expenditures on fuel and carbon costs). Both of these marginal benefits diminish as more renewable resources are added to the system.

Capacity value declines because as large amounts of renewables are installed, they reduce the residual load during the times when they are most readily available, and shift the residual peak to hours when renewable power is less abundant. Once the residual peak has been shifted to a low-wind or low-sun hour, each additional megawatt of renewable capacity will contribute less toward reducing the remaining peak load requirement. The blue line in Figure 25 illustrates this phenomenon.

Before I continue, I should explain how I prepared the figures in this section. I began with the optimal generation portfolio for a $30/tCO₂ carbon cost, which included 1.6 GW of solar troughs, 280 MW of photovoltaics and 35 GW of wind farms in the

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23 The “residual load” is defined as the system electricity load in each hour, less the production of power from renewable energy systems during the same hour. This is the load that must be served by conventional generators, and the peaks of this load determine how many conventional generators are needed to maintain adequate generation capacity in all hours.
2022–25 investment period. I then forced the model to develop 0–60 GW of solar troughs by 2022–25, in steps of 500 GW, re-solving at each step. During this process, investment in wind farms and photovoltaic systems was held constant at the original optimal level, but the optimizer was free to adjust investments in natural gas plants and transmission lines, and operation of existing and new equipment, to make the best use of these solar facilities. At each step, I recorded the number of megawatts of solar and natural gas generators and transmission lines that were built, the number of megawatt-hours of power produced by solar and gas plants, and the expenditures on plants, transmission lines, fuel and carbon costs. This made it possible to see the marginal change in the optimal amount of other system resources, in response to changes in the amount of solar troughs installed in the system.

Continuing the previous discussion, the blue line in Figure 25 shows how many gigawatts of natural gas power plants can be eliminated from the optimal power system, for each gigawatt that the solar capacity is increased. The first 1.5 GW of solar facilities provide about 87 percent of their nameplate rating during the system’s peak hour, so they are able to displace about this much natural gas generation capacity. However, as solar power production increases, the residual peak load shifts to different hours, when less solar power is available, and the marginal capacity contribution diminishes, eventually reaching zero for plants installed above the 4 GW level. At this point, the residual peak falls during a sunless hour, and additional solar troughs can do nothing to reduce it.
Figure 25. Marginal energy and capacity contributions as solar capacity is increased

The upper, red line in Figure 25 shows the marginal reduction in power generated by natural gas plants, in response to each additional MWh generated by solar facilities. For solar capacity up to about 1.5 GW, the system is able to use every MWh that is generated. However, above this level, the system begins to have too much power during the hours when solar electricity is available. At this point, the optimizer begins to shed this surplus solar power, so that as solar capacity is expanded from 2 to 35 GW, only 80-90 percent of the additional solar energy can be used to offset natural gas power production.

The marginal contribution of usable megawatt-hours jumps up and down (and has a large spike around 37 GW) principally because of the normalization used for this graph. As the installed capacity is stepped up to higher levels (e.g., from 36 to 37 GW), the optimizer sometimes chooses to reconfigure the solar portfolio to provide less incre-
mental power, but at more useful times. This reduces the incremental number of mega-
watt-hours produced when the total capacity is stepped up, so that the incremental num-
ber of *useful* megawatt-hours per number of megawatt-hours *produced* jumps suddenly
upward.

Once solar capacity exceeds 35 GW, loads become completely satisfied by solar
power during more and more of the hours when it is available. Consequently, the mar-
ginal contribution of useful power drops off precipitously, becoming negligible around
60 GW of nameplate capacity. At this point, loads are completely satisfied by renew-
ables during all sunny hours, and any additional solar plants would only produce surplus
power.

The erosion in the capacity and energy contribution from solar power plants has a
direct effect on their economic benefits. Figure 26 shows the marginal benefits of each
additional MWh produced by solar power plants. Here, the benefits-per-solar-MWh are
defined as the amount by which other costs can be reduced when enough solar troughs
are added to generate one more MWh of electricity per year. They are found by calculat-
ing $(\text{cost}_{\text{category } i, \text{ step } n-1} - \text{cost}_{\text{category } i, \text{ step } n})/(\text{solar MWh}_{\text{step } n} - \text{solar MWh}_{\text{step } n-1})$, where “cost-
$\text{category } i, \text{ step } n$” indicates the total system cost in some category (e.g., capital payments for
natural gas plants), when solar nameplate capacity is at step n (e.g., 1.5 GW, 1.7 GW,
etc.), and “solar MWh$_{\text{step } n}$” indicates the amount of solar electricity produced at that
step. That is, the benefits per MWh are defined as the marginal cost savings divided by
the marginal energy production, when comparing two different levels of solar invest-
ment.
The economic value of capacity savings are shown in blue. They start around $25 per MWh of solar power, and drop as solar plants become less able to displace natural gas plants from the grid. Savings in fuel costs make up a much larger share of the benefits of additional solar power. They drop slowly as solar power investments increase from 0 to 35 GW, as additional solar capacity begins to displace more efficient gas plants, instead of less-efficient, older plants that are used during peak hours. Above 40 GW, they fall more quickly, as solar stops displacing any gas energy from the power supply. These later decreases in benefits are directly proportional to the increasing production of surplus power in this range. Carbon costs follow a similar trend to the fuel costs. In the 18–35 GW range, the optimal portfolio begins to include some transmission capacity to take
advantage of solar energy; this produces a small “negative benefit” of $0–$10/MWh. Around 37 GW of total capacity, the optimizer reconfigures the solar portfolio to use sites that produce power in more useful times and/or locations, but produce less power overall. Consequently, the marginal energy contribution drops, and the marginal benefit per unit of energy rises; the system also reduces investments in transmission at this point.

![Figure 27. Cost and benefits of additional solar power facilities](image)

In Figure 27, I add together these economic benefits of solar power facilities, and also show the cost of building new solar plants, all in dollars per MWh. I have combined fuel benefits with expenditures for transmission lines, because the model tends to trade-off between these two categories of expense. With my projected costs for solar power, and a $30/tCO₂ carbon cost, it is clear that capacity benefits are important to the development of solar power. I noted previously that the optimal investment plan under these
conditions includes 1.6 GW of solar thermal troughs. 27 makes it clear why the optimizer chose this level: up to this level of investment, the benefits of additional solar capacity exceed their costs, but beyond this point, they are lower than the costs. (The cost of solar power per MWh produced jumps up and down due to the same normalization problem discussed earlier, but this does not affect the fundamental conclusion.)

To complete the picture, I now turn to the costs and benefits of wind farms. Figure 28 shows the marginal contribution of usable energy and firm capacity for incremental wind capacity from 0 to 46 GW (the maximum available in these scenarios). Figure 29 shows the marginal cost and benefits of wind power in this range of capacities.

![Figure 28. Marginal benefits of additional wind power plants](image)

The system is able to use all the wind power produced by wind farms up to about 35 GW of capacity. This is much higher than was found for solar power, largely because
wind power is available at a more diverse range of times. The incremental capacity benefits of wind farms start out lower than they do for solar thermal troughs, but drop off less quickly. This is because wind power is not concentrated during a few peak hours of the day.

![Figure 29. Cost and benefits of additional wind capacity](image)

Wind power is less expensive than solar power, and its capacity and energy benefits are retained up to a much higher penetration level. Consequently, it is cost-effective to build more wind power than solar. Figure 29 shows that the marginal cost per megawatt-hour of wind power tends to rise gradually, as the investment plan starts with the windiest sites and then incorporates less windy sites. However, the marginal benefit per megawatt-hour also holds steady or even rises slightly, as the power from these less-windy sites comes at more useful times. Eventually, around 35 GW of nameplate capac-
ity, wind farms begin to produce surplus power during some hours, and their cost-effectiveness drops off rapidly.

The limiting factor for wind power appears to be a combination of a shortage of good wind sites (a somewhat artificial feature of my analysis), and an increase in the generation of surplus power above a certain penetration level, which leads to a steady decline in the fuel and carbon benefits. This contrasts with solar power, for which the limiting factor (at least at $30/tCO_2$ carbon cost levels) appears to be the decrease in capacity benefits.

These analyses suggest that investment in intermittent renewable energy systems can be limited by two important factors. If the cost of the systems is high, or carbon costs are low (as is the case for solar troughs with a $30/tCO_2$ carbon cost), then investment may be halted by diminishing capacity benefits. On the other hand, if the costs of renewable power are low, or carbon costs are high (as is the case for wind energy in most of the scenarios I consider), then the key limit is likely to be the production of surplus power. This can be considered a more fundamental limit than the lack of capacity benefits for two reasons: (1) fuel and carbon benefits are generally a much larger share of the value of renewable energy than are the capacity benefits, so their decrease is relatively more important; and (2) if a renewable generator produces no capacity benefits, it can always be “firmed up” by installing relatively low-cost gas generators, even if they are not used often; however, once wind or solar power reaches the point where a large share of its production is surplus, then the carbon and fuel benefits will drop off rapidly, and there is no way to make them up from another source.
The surplus power problem is also likely to be more significant in the future – as the cost of renewable technology drops, the marginal cost line in Figures 27 and 29 will move down, and the optimal amount of wind or solar power (the point where the cost and benefit lines intersect) will move further to the right, into the region where declining fuel and carbon benefits become the limiting factor. Similarly, if we care very strongly about reducing greenhouse gas emissions, which would be represented by increasing the carbon cost (the width of the green band in Figures 27 and 29), this will also move the optimal investment out to the point where it is limited primarily by the surplus power problem.

Much previous attention has been focused on the capacity benefits of renewable power systems, with an implicit assumption that they cannot be economically developed beyond the point where their capacity contribution begins to decline. There also appears to be some unease with the idea of assigning any firm capacity value to intermittent renewable power systems, especially within the power system engineering community. These intuitions may explain why most renewable energy policies enacted to-date have set targets in the range of 20 percent or less of the energy supply, roughly corresponding to the size of reserve margins. There may be a sense that “renewables are OK, as long as we have some backup power, and we generally have about 15-20% backup power, so that’s the right level.”

However, my analysis suggests that much of this attention on capacity benefits may be misplaced. For resources that are just beginning to be competitive with conventional power sources (such as solar thermal troughs), the capacity benefits may be important to economic viability. However, capacity benefits are a relatively small part of the value of renewable power systems, and their decline appears to be less important than the
“surplus power” problem in limiting the deployment of renewable energy systems. A serious effort at climate change could easily set a carbon cost as high or higher than the capacity benefits of renewable power systems, overcoming any decline in these benefits. This suggests that it may make more sense to think of renewables as energy savers rather than capacity savers; if we are serious about climate change, it will be cost-effective to invest in renewables on a large scale, even if we also have to invest in conventional plants to provide backup power during peak hours. Chapter 6 showed that this is indeed the course chosen by the Switch optimizer, as carbon costs are increased.

No matter how high the carbon cost is set, it cannot make intermittent renewables the best choice for 100 percent of the energy supply. As renewable deployment increases, the share of unusable power will also increase, and the fuel and carbon benefits of additional renewable energy systems will inevitably decrease to the point where they become uneconomical. This suggests that rather than focusing policy efforts on reducing peak-hours electricity loads, or developing resources that provide extra power during hours of peak demand, it may be more valuable to look for ways to solve the “surplus power” problem, making economical use of off-peak power from renewable sources. I take a first look at this possibility in Chapter 9.

7.2 Benefits of Aggregating Diverse Locations and Technologies

A number of studies have found that wind power production varies at least partially independently at spatially dispersed sites, so that the combined power output from many different wind farms would be more reliable than the output from any single farm. Based on this finding, they have suggested that spatially dispersed wind resources may be more useful for the power system than wind from any one site. A similar argument could
be made for spatially dispersed solar sites, at least during daylight hours, and an even stronger argument might be made for combining wind and solar resources, to provide even greater diversity. Little or no attention has been given to the solar side of this concept, probably because solar power has historically been expensive, and previous studies have not contemplated adding large amounts of it to the power system.

In Section 7.1 I discussed the two factors that may limit the adoption of renewable resources: providing too little power when it is needed (the capacity problem), or providing too much power when it is not needed (the surplus-power problem). Previous discussions of the benefits of geographic smoothing have focused on the improvement in capacity contribution, but it is also plausible that carefully combining different sites and technologies could also help reduce the surplus-power problem. However, no study has previously examined the effect of spatial and technological aggregation on the amount of renewable power that can be used economically in the power system. This section investigates that question.

I investigate this question by running the Switch model with five different sets of possible renewable power projects. These sets are listed below:

1. All wind sites that have been identified in California
2. All solar trough sites in California
3. A wind power “mega-site” – a single site with a capacity limit artificially set equal to the total amount of wind capacity used in portfolio 1 (46 GW)
4. A single solar trough site with unlimited room for solar troughs
5. All wind and solar trough sites in California

Figure 30 shows the results of these runs. They show that for any carbon tax, the system builds much more wind power at the single “mega-site” than it would when
choosing from all known sites, with their normal capacity limits. It is not possible to conclude much from this, except that the state is able to absorb quite a lot of wind power even if different sites are highly correlated; \textit{i.e.}, for wind, there does not appear to be much benefit to geographic aggregation – instead it may be more important to develop good sites, wherever they are. For solar power, geographic smoothing does appear to provide some benefit: the optimal power portfolio includes more solar power at all carbon costs if it can choose from among the full spectrum of sites, instead of building only at a single sunny site. This suggests that the state’s solar resources in aggregate may be more useful than would be assumed by looking at the time series of power production from any single site.

However, the biggest benefit appears to come when both wind and solar sites are combined. In this case, the optimal portfolio generally includes nearly all available wind power, but it also includes a substantial amount of solar power. Wind and solar power are available at highly complementary times in California, and together, they are able to contribute up to about 50 percent of the state’s power requirements at a marginal cost of $200 or less per ton of CO$_2$ avoided. This is about 20–25 percent more than either of the could contribute alone.
Figure 30. Optimal share of electricity supplied by wind, solar or both, in 2022–25, with carbon costs of $0–200/tCO₂

Figure 31 shows the complementarity between wind and solar in a different way. Here, we see that the “emission reduction frontier” for power from a single solar site is confined to the upper, left corner of the plot – it is impossible to achieve large emission reductions at a low average cost of power. When multiple solar sites are combined, this frontier moves down and to the right, making it possible to achieve greater emission reductions and/or lower power prices.

Wind plants are less expensive than solar facilities and provide power at more times of the day, so the “emission reduction frontier” for the known collection of wind sites comes at a lower price than solar. Unfortunately, only a limited number of wind sites are modeled in this scenario, and a hard limit of wind capacity is reached around 50 percent of the state’s power demand. Interestingly, in this region, even though solar sites
are more expensive than wind, the average cost of power can be brought down by adding some solar to the wind portfolio (the green curve begins to dip below the blue curve). In addition, when wind and solar are combined, it is possible to continue the emission reduction frontier begun by the wind sites, yielding much greater emission reductions than can be achieved with either wind or solar alone, and at a substantially lower cost than would be possible with solar alone.

Figure 31. Minimum cost of power while reducing emissions in 2022–25, with carbon costs of $0–200/tCO₂, using wind, solar or both
CHAPTER 8: OTHER SENSITIVITY STUDIES

8.1 Introduction

The Switch model relies on a number of assumptions about the costs and quantities of resources available to the power system in future years. In previous chapters, I have used a single, “best-estimate” value for many of these assumptions. In this chapter, I investigate how the optimal design of the power system would change if different assumptions are used for several of these parameters, for example, if the cost of fuel or generators differs from my assumptions, or if the system is able to take advantage of elastic demand for electricity or customers who are willing to have their loads curtailed during peak hours.

8.2 Fuel Prices

Forecasted fuel prices are one of the key assumptions driving the Switch model’s choice of resources to use in a future power system. To investigate how important these costs are to the system design, I re-run the model using forecast prices for all fuels that are 50 percent below or above my base case assumption in all years. Figure 32 shows the supply curve prepared using these cost assumptions. With lower fuel prices, a more gas-intensive power system becomes a preferred option, especially with low carbon costs. On the other hand, with higher fuel prices, a highly renewables-intensive system design becomes the preferred option, yielding over 60 percent emission reductions relative to 1990, even without a carbon cost, and quickly rising to 80 percent or more for carbon costs above about $50/tCO₂.
Figure 32. Emission reduction supply curve with fuel prices 50 percent above or below base-case forecast

Figure 33 shows the average cost of electricity during the final study period (net of any carbon cost), while achieving various levels of emission reduction, under each of these fuel-cost scenarios. With the reduced fuel costs, power becomes cheaper across the board, and it is possible to achieve any level of emission reduction while keeping costs lower than they would be in the other scenarios. As fuel prices rise, the cost of power increases, and the range of emission reductions that would be achieved between $0 and $200/tCO₂ carbon costs becomes narrower and higher.
Figure 33. Direct cost of electricity, while achieving various levels of emission reduction, with fuel prices 50 percent above or below base-case forecast

It may be worth noting that the right edges of the higher-cost curves would involve radical reductions in natural gas use from today’s levels, so they would likely yield lower gas prices than would otherwise be expected. Consequently, a high-renewables future could, in a way, be self-financing. Since the Switch model does not directly incorporate the supply elasticity of natural gas, I have not investigated this possibility in any detail.

8.3 Equipment Costs

Another key driver of the Switch model’s investment choices is the projected capital cost of generation plants. As discussed in section 4.6, the capital costs of renewable plants have been falling faster than natural gas plants, a trend which I project into the future in my base case. In addition, the cost of electricity from natural gas plants is dominated by the cost of fuel, which is projected to rise over time. These two trends are forecast to make renewable resources increasingly competitive in future years. In this section, I consider how the outlook would change if equipment costs fall more slowly or quickly than assumed in the base case.
Figure 34 shows the emission reduction supply curve when annual capital cost improvements range from 0 to 200 percent of the base-case assumptions, and Figure 35 shows the cost of power while achieving various emission reductions, under these same assumptions. Not surprisingly, if technological progress is stalled, so that costs of renewable (and fossil) generators remain at their 2007 level, the optimal generation portfolio ends up achieving lower emission reductions for any given carbon cost, and if progress is accelerated, emission reductions become easier.
Figure 35. Direct cost of electricity, while achieving various levels of emission reduction, with generator cost improvements at 0–200 percent of the base-case rate

Several other points are worth noting about these figures. (1) Even if technological progress is completely stalled, it is still possible to achieve significant emission reductions while changing average electricity prices by less than 15 percent. (2) Technological progress brings down power prices across the board, even if no cost is assigned to carbon dioxide emissions (the left edges of the power price curves drop steadily as progress accelerates). This suggests that it would be good policy to try to lower the cost of renewable energy equipment, whether or not one believes climate change is a pressing concern. And (3) if technological progress could be accelerated by a factor of two, it would open the way for emission reductions on the order of 75 percent below 1990 levels, while maintaining power prices at the base-case no-tax level (around $76/MWh).

I also note that as with natural gas prices, there is potentially a negative feedback between expansion of renewable energy in the state and declining costs for renewable energy equipment. Expansion of the renewable energy sector in California (especially if it is
in concert with other parts of the U.S. or world) can provide economies of scale and learning-by-doing that accelerate improvements in the price of power.

8.4 Elastic Electricity Demand

For most of the work reported here, I assume that electricity demand is completely inelastic – that electricity loads in each hour are fixed at the baseline levels described in section 4.4. This is done in large part to ensure that my results are conservative and transparent – that the Switch model builds a system that provides exactly the amount of power that people currently expect to need, rather than relying on customers to reduce their loads in response to high electricity prices. This assumption may be reasonably accurate for scenarios with low carbon costs, or if a policy framework is envisioned where the compliance costs of a carbon dioxide tax or cap-and-trade system were refunded to ratepayers proportionately to the amount of power they consume (so that their only increased cost would be the direct costs of building a higher-renewable system, but the carbon tax would have relatively little effect on the marginal price they pay per kWh).

However, this assumption is not entirely realistic or environmentally optimal. Ideally, the cost of carbon dioxide emissions should be factored into the price that customers pay for each unit of electricity they consume (even if it is separately refunded to consumers as a reduction in the fixed component of each bill or a reduction in income tax rates). Then customers would only consume the electricity that they actually considered it worthwhile to consume, including the cost of carbon dioxide.

In this section, I investigate the effect of sloping demand curves on the emission reductions possible from California’s electric power system. For this set of sensitivity studies, I use sloped demand curves with elasticities of 0 (the base case, in which demand
is unaffected by price) to -0.78 (in which case a 1 percent increase in the annual average cost of power induces a 0.78 percent decrease in the year-round loads). For these studies, the minimum and maximum possible demand are assumed to be 74 percent and 126 percent of the baseline demand, respectively.

These elasticities center around -0.39, which is Reiss and White’s (2005) estimate of the long-term elasticity of household demand for electricity. They also fall in the range of -0.09 to -0.845 reported by a number of other studies (Lijesen 2007).

Figures 36 and 37 show the emission reduction supply curve and the cost of power while achieving various emission reductions, when these demand elasticities are in effect. In these scenarios, annual average power costs are slightly higher than they were in 2005, so demand elasticity tends to lead to reduced consumption of electricity, and lower emissions than would otherwise be expected. Demand elasticity allows for substantial emission reductions with little change in the cost of power, or, conversely, it can allow for significant reductions in the average price of electricity while achieving any given emission target (e.g., 70 percent reductions from 1990 levels). This is especially true at higher carbon taxes.
In previous parts of this thesis, I have assumed that demand-response resources are not able to participate in California’s markets for firm electricity capacity. However, capacity markets in the PJM and ISO New England regional transmission areas have recently been opened to participation by energy-efficiency projects and inter-
ruptible loads, and it is possible that similar opportunities could be created in California in the future.

It is difficult to judge how much interruptible load would be available to provide reserve capacity in California at various price levels – i.e., the supply curve for demand response – because there is presently no market for this service. For this set of sensitivity studies, I assume that the supply of interruptible load rises from 0 percent of the peak load at $0/kW-year, up to 5% of the peak load at $95/kW-year, or potentially at prices 50 percent higher or lower than this level.

This supply elasticity of 1% of peak load per $19/kW-year is derived from the ISO NE and PJM capacity auctions: The ISO NE forward capacity auction for 2010/11 cleared 978 MW of interruptible load at a price of $4.50 per kW-month (ISO NE 2008). These values correspond to 2.9 percent of its peak load requirements, at a cost of $54 per kW year, respectively. PJM’s Reliability Pricing Mechanism Base Residual Auction for 2008/09 cleared 3489 MW of interruptible load (2.1 percent of PJM’s peak requirements) at a price of $111.90/MW-day ($40.84/MW-year) (Ott 2008). Dividing the marginal price of $54/kW-year by 2.9 percent of peak load yields an approximate slope of $18.6/kW-year/% for ISO NE’s supply curve for interruptible load. Dividing $40.84/MW-year by 2.1 percent yields a slope of $19.4/MW-year/% for the supply of interruptible load in PJM.

By operating the Switch model with these supply curves for load interruption, I obtain the emission reduction supply curve and power costs shown in Figures 38 and 39. The economic benefits of interruptible load are not as high as one might expect, i.e., not as high as the full capital cost of new gas plants. This is because if the system adopts interruptible load and foregoes building additional gas plants, it ends up running older
gas plants more of the time, and paying more for fuel, which negates much of the savings in capacity costs. Consequently, the Switch model takes advantage of very little interruptible load (around 2.5 percent of peak load at low carbon costs or 1.75 percent at high carbon costs), and the effect of interruptible load on carbon dioxide emissions or power prices is nearly indetectable.

Figure 38. Emission reduction supply curve with and without interruptible load bidding

Figure 39. Direct cost of electricity, while achieving various levels of emission reduction, with and without interruptible load bidding
8.6 Energy Efficiency

The next sensitivity study investigates one final effect that can affect demand for electricity – active programs to promote energy efficiency. A number of studies have developed supply curves for load reductions via energy efficiency. These generally indicate that there are measures that could be undertaken to reduce electricity loads by as much as 45 percent at costs below the current price of electricity. These are the maximum possible savings, but only a fraction of these would be likely to be achieved by real-world policy measures. These studies also generally report that there are a range of measures with different marginal costs, some of which would cease to be cost-effective if electricity prices fell, and others of which would become cost-effective if electricity prices rose. Taken together, these characteristics can be seen as describing an alternative demand curve for electricity: effective policies could shift the demand for electricity at current prices to the left by some fraction between 0 and 45 percent. Once there, the annual demand for electricity would rise or fall in response to the price of power, as different efficiency measures become uneconomical or more economical. These studies generally show a slope of about -20 percent at the new demand level – e.g., an increase in price of 10 percent could make it cost-effective to adopt efficiency measures that reduce demand by a further 2 percent. This -0.2 elasticity appears to hold roughly constant across the whole range of available efficiency measures, so that at low prices, and high demand, small-magnitude changes in price can induce large-magnitude changes in consumption, while at high prices when demand is already low, large-magnitude changes in price are needed to induce even small changes in demand.

With this in mind, I model the effect of energy efficiency measures as a transformation of the demand curve for electricity: I first reduce the baseline demand by 0-30 percent, relative to the level originally described in Section 4.4 (these reductions in the
baseline demand are phased in gradually over the course of the four study periods). I then pass a sloping demand curve through the new baseline load level, with an elasticity of -0.2 at all points. This curve allows demand to drop by up to 10 percent from the new level, or increase by up to 30 percent from the new level, depending on the annual average cost of electricity.

Figures X and Y show the carbon cost and average electricity cost that would be needed to achieve various levels of emission reduction in the California power system, with these efficiency-based demand curves. (The difference between the “base case” and the “0% reduction” case is simply that the 0% reduction case uses the -0.2 elasticity of demand, while the base case assumes inelastic demand.)

It appears that strong efficiency programs could significantly help reduce greenhouse gas emissions from the power system, especially at low carbon cost levels. For example, reducing demand by 30 percent with no carbon tax could have about the same effect on the emissions from the optimal portfolio as imposing an $80/tCO2 carbon dioxide tax.

![Figure 40. Emission reduction supply curve with various levels of energy efficiency](image-url)
Figure 41. Direct cost of electricity, while achieving various levels of emission reduction, with energy efficiency reducing demand by 0–30 percent

8.7 Transfer Capability of Existing Transmission Network

Another potentially important set of assumptions in the Switch model concern the amount of transfer capability available from the existing transmission network. If I have overestimated this capability, or if capabilities are dramatically reduced by the new generation plans proposed by the Switch model, then my analysis may overlook upgrades that are necessary in order to achieve high levels of emission reduction. To test this possibility, I de-rated the transfer capability of the existing transmission network by amounts ranging from 0 to 30 percent below the amounts I assumed in the base case, and then re-ran the Switch model with this de-rated capacity.

As shown in Figures 42 and 43, these changes had minimal effect on the cost or emission-reduction potential of the optimal portfolio. In the base case, the power system is assumed to begin with about 24,000 GW-km of transfer capability, and the Switch model adds another 700 GW-km. In the 30-percent-derated case, the system starts with 17,000 GW-km of transfer capability, and the Switch model adds another 1,700 GW-
km; decisions about where to place this extra capacity do not seem to significantly affect the design of the optimal power system. It is surprising that the model builds so little transmission in either of these cases; this suggest either that the existing system is more than adequate to provide for most power needs in coming decades, or that I have grossly overestimated its capabilities.

It also appears that transmission costs are simply too low to make much difference to the Switch model's power system design. The difference between the average cost of power in the three cases shown in Figure 43 is due almost entirely to the reduction in the capacity of the existing network. The Switch model includes all existing power lines as a sunk cost, which must be paid for at the same rate as new power lines, so when I de-rate the existing lines, it reduces the costs that must be paid for these lines. A 30 percent reduction in the size of the existing network appears to yield a change in cost on the order of $2/MWh in the average cost of power. This suggests that even if the model had to rebuild the entire network from scratch, it would only add $5–10 per MWh to the cost of power. This cost is much smaller than the cost of fuel or capital repayments for generators, so it is unlikely ever to become a dominant factor in the model's investment decisions.

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24 This can easily be checked to a first order approximation: The California power system as represented here has about $24 \times 10^6$ MW-km of transmission lines, which cost about $1000$/MW-km, and have a capital recovery factor around 10%, yielding a carrying cost around $2.4 \times 10^9$ per year. The system also has average loads around $40,000$ MW x $8760$ h/year = $0.35 \times 10^9$ MWh/year. Dividing gives a transmission cost around $6.90$/MWh.
The next sensitivity test investigates how the optimal investment portfolio changes as the cost of new transfer capability varies from my base-case assumptions. Here, I have varied the cost of new transmission lines between $700/MW-km and $3000/MW-km, compared to my base-case assumption of $1000/MW-km. These
costs apply both to inter-zonal transfer capability, and to the tie-lines to connect new solar and wind facilities to the nearest interconnect point. Figure 44 indicates that these variations in cost have a minimal effect on the emission reductions that can be obtained from the power system. Interestingly, even when new inter-zonal transmission is completely banned, the system is still able to achieve nearly the same emission reductions, using the existing inter-zonal network. As in the section 8.7, this suggests either that the transmission network already has ample transfer capability, or that I am overestimating its capabilities.

![Figure 44. Emission reduction supply curve with transmission costs between $700/MW-km and $3,000/MW-km](image)

Figure 45 is not very revealing in this sensitivity study: most of the cost difference between the different scenarios can be explained by the difference in carrying-cost for existing lines. As noted in section 8.7, paying $1000/MW-km for the existing network corresponds to about $7 per MWh of electricity produced. So when the book value of the existing network is increased by $2000/MW-km, this increases the cost of electricity by $14/MWh. Thus, the differences in cost between the scenarios shown in Figure 45
are simply artifacts of the way I ran the Switch model for this study. In the future, I may re-run this study, using one (fixed) value to account for the sunk costs of the existing transmission network, and a different value to indicate the cost of new transmission lines.

![Figure 45. Direct cost of electricity, while achieving various levels of emission reduction, with transmission costs between $700/MW-km and $3,000/MW-km](image)

8.9 Length of Study Period

Costs of fuel and equipment beyond the 2025 timeframe are even more uncertain than costs over the next two decades. For this reason – and to save computing time – all the analyses reported in this dissertation have looked only at costs and benefits incurred over the period of 2010–25. By spreading costs evenly over the life of each power plant, I have ensured that the model uses a “pay as you go” approach, so that there are no payments within the study period to pay for equipment that still exists after the end of the study, nor is any equipment used during the period and only paid for after the study. I have also used a loose argument to say that “if a particular power system investment plan is optimal for the period up to 2025, it should also be nearly optimal for the period after that.” However, this argument is difficult to prove, so I next run the Switch model with a
32-year investment period. In this case, I have used exactly the same weather conditions for the second 16 years as I used for the first 16, to ensure that the only factor changed is the length of the study. I then compare the optimal investment plan as of 2022 from this long-term study to the one developed using the 16-year version of the model. The results of this analysis are shown in Figures 46 and 47.

Figure 46 shows that a 32-year analysis indicates that renewable energy investments should be delayed later than the 16-year study indicates (i.e., when Switch considers all 32 years, it reduces the amount of renewable energy it uses during the first 16 years).

This appears to be partly due to the fact that the cost of renewable energy projects are assumed to continue falling during the second half of the longer study. The system is only able to build and use a finite amount of wind and solar projects, so it defers these investments until a later investment period, when they can be built less expensively. Some evidence for this is given by the fact that the 32-year investment plan includes more renewables in the first half if the cost of generators is frozen after the 16th year (i.e., the red line in Figure 46 is further to the right than the green line). However, this cannot be the only explanation, because the investment plan for the first 16 years of the 32-year study remains more gas-intensive than the 16-year study, even if costs are frozen after the 16th year.

Another explanation could be that when the system must meet high future loads, it is cost-effective to build new natural gas plants early, so that they can be used to displace older, less-efficient gas plants earlier in the study. This then makes it more economical to defer renewable energy investments until later in the study. This possibility could be tested by freezing loads for the last 16 years, which I have not done here.
At any rate, this finding suggests that the plans recommended by the Switch model elsewhere in this dissertation may include a little more renewable energy than is actually optimal.

Figure 46. Emission reduction supply curve in 2022, with 16-year or 32-year study period

Figure 47 tells a somewhat different story. It indicates that the direct cost of reducing emissions by 2022 is nearly the same, regardless of whether we use a 16- or 32-year study. This is not surprising, since, by definition, any emission reductions achieved by 2022 will require investments in equipment by that date – nothing that happens in later years would be expected to affect the cost of reducing emissions in 2022.
The final sensitivity study focuses on assumptions about the retirement date of power plants. As discussed in Section 4.8.1, all the other analyses in this dissertation have assumed that existing power plants are retired (somewhat arbitrarily) at the end of the typical lifetime for that type of plant. In reality, it may be possible to extend the life of these plants, and thereby defer investments in new power plants. To test this possibility, I optimized four additional scenarios in the Switch model. First, I forced all power plants that existed as of 2007 to continue in operation through the end of the first study period (2010–2014), even if they are already beyond their expected retirement age. Then I added four years to the life of these plants, as well as others that would have otherwise be expected to retire at some point during the study period. I repeated this until all existing plants were kept operational all the way through the study.

Figure 48 indicates that extending the life of power plants up through the middle of the study period has little or no effect on the emission reductions available up to each marginal carbon cost level. However, extending the lives of existing plants into the last
half of the study can tend to drive renewables out of the system, particularly when carbon costs are below $50/tCO₂. This is probably because extended-life power plants act as zero-cost competitors to new renewables many of which are generally built during the last eight years of the study. When carbon costs are low, this competition is especially close, and the old plants tend to displace investments in new renewables.

Figure 48. Emission reduction supply curve in 2022, with 16-year or 32-year study period

Figure 49 indicates that these plant life extensions also have minimal effects on the cost of power when achieving various levels of emission reduction. Even the slight difference that is visible for the 8- and 12-year extensions is probably an artifact of the way this scenario is treated by the Switch model. When plants’ lives are extended, the model continues to use the same carrying cost for them every year. This cost is fixed through the whole scenario, so it does not affect other investment decisions, but it does raise the average cost of power for the scenario, especially if these plants are not used much.
Figure 49. Direct cost of electricity, while achieving various levels of emission reduction, with 16-year or 32-year study period.
CHAPTER 9: TOWARD A VERY LOW-CARBON POWER SYSTEM

9.1 “High-Renewables” Scenario

The previous chapters have explored the range of emission reductions that are possible from the power system, using existing technologies and a fairly limited set of potential wind farm sites. In this chapter, I make a first exploration of how far emissions could be reduced under a less conservative set of assumptions. Encouragingly, I find that, with a concerted effort, it appears possible to provide all the electricity needed for traditional electricity loads, and to replace about two-thirds of the gasoline used for transportation in California, while reducing greenhouse gas emissions by more than 80 percent compared to the 1990 level.

For this “high-renewables” scenario, I change three of the assumptions used in earlier chapters.

1. I first increase the number of wind turbines that can be built at each wind farm site by a factor of five. This corresponds to assuming that additional wind farms could be built with exactly the same timing and location as the ones previously used in the Switch model. This is intended to be a simple way of accounting for the possibility of using additional wind sites that were not analyzed by the Intermittency Analysis Project, and not previously included in the Switch model. As noted in section 4.9.1.2, the sites already used in the Switch model correspond to only about 10 percent of the state’s gross high-wind sites. Increasing this by a factor of five, to 50 percent is ambitious, but not an unrealistic possibility. It is also conservative to assume that these additional wind sites have the same timing as those already in the Switch model; in reality, previously unstudied sites are likely to add more diversity (and load-carrying capability) to the power system than would a set of sites identical to the known ones.
2. I next require the power system to provide enough additional electric power to charge half of California’s current gasoline vehicle fleet, if it were converted to electric or plug-in hybrid-electric vehicles (PHEVs). This corresponds to an additional average load of 10.5 GW, which is phased in from zero in the first study period to the full level in the last study period. The geographic distribution of these loads is assumed to be proportional to the already forecast annual electric loads (this acts as a crude proxy for the density of population and economic activity). I test the effect of these extra loads in two different modes: First I assume that vehicles are charged at random hours of the day, so that they impose a uniform extra load of 10.5 GW on the system at all hours and dates. Second, I allow the Switch model to select the best hours to charge these vehicles, but require that all vehicles must be charged every day, so that the vehicles require 10.5 x 24 GWh each day, but the Switch model chooses when those hours occur. This corresponds roughly to a system where electric vehicles are charged on real-time tariffs, and customers have perfect flexibility in when they charge their vehicles, and perfect foresight of when the least-expensive charging times will occur.

Some of these vehicle assumptions are conservative, and some liberal. For example, it is unclear how well customers will be able to identify or take advantage of optimal charging hours. On the other hand, customers may choose to use gasoline instead of

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25 I arrive at this 10.5 GW figure as follows. EIA reports that California used 383,178,000 barrels of gasoline in 2006. This corresponds to a heat content of 67 GW. I assume that gasoline vehicles are 25 percent efficient at converting this heat to work, so that this gasoline does 16.8 GW of work. Then I assume that electric vehicles are 80 percent efficient at converting electricity to work, so that they will need 20.9 GW of electricity to do the same amount of work. I then divide by 2 to obtain the target above. This calculation does not account for the additional efficiency improvements that would be obtained when this part of the fleet is converted from traditional gasoline engines to hybrid drive systems. If those improvements are included, this amount of electricity may be enough to serve about three-quarters of the current gasoline vehicle fleet, or half of a larger, future fleet. I consider only gasoline vehicles because they are generally used for shorter periods each day than diesel vehicles, making them better candidates for electrification.
electricity on days when electricity capacity is constrained around the clock, so my assumptions may impose an unrealistically severe requirement for firm generation capacity.

3. Finally, I assume that a serious effort is undertaken to conserve electricity, either in response to higher prices, or via increased investment in energy efficiency measures. The result is that demand elasticity is set at -0.2, and baseline electricity loads are shifted 20 percent lower than the baseline forecast by 2022–25 (this is identical to the 20 percent load reduction case discussed in section 8.6). This keeps loads approximately flat at the 2010 forecast level, instead of rising by about 2 percent per year as shown in the baseline forecasts in section 4.4.

### 9.2 Effects on Emission-Reduction Supply Curve and Power Costs

Figure 50 shows the effect of each of these changes on the emission reduction supply curve. Unlike previous sections, the baseline for this supply curve is the sum of the 1990 emission levels due to the state’s electricity consumption (86.7 million tCO₂) and for half of its gasoline consumption (56.5 million tCO₂). The discovery of additional wind sites allows additional emission reductions of about 5–10 percentage points at all levels of carbon cost, as the system takes advantage of this low-cost resource.

If we then consider charging PHEVs from the power system, there is a sharp reduction in emissions, as half the state’s gasoline demand is replaced by mostly-renewable electricity. Interestingly, the optimal power grid derives about the same share of its power from renewable sources whether vehicles are charged around-the-clock or just at the most preferred times, so the emission savings are about the same for the uniformly-charged and optimally-charged cases.

Finally, the 20 percent reduction in traditional loads (on top of the increased access to wind and the use of PHEVs) allows for a further 5–15 percent reduction in emis-
sions, yielding a power system that could emit 59–88 percent less greenhouse gases than were released when providing the same services in 1990.

Figure 50. Emission reduction supply curve with additional wind sites, plug-in hybrid-electric vehicles and reduced electricity loads

Figure 51 shows the cost of producing electricity in each of these scenarios. These curves can be thought of as a sort of “efficient frontier,” showing the lowest power cost that can be paid while achieving each level of emission reductions. Ideally, we would like the system to move as far to the lower, right corner as possible, with low power costs and high emission reductions.
Here we see that the addition of more wind sites both shifts the cost of power down and increases the amount of emission reductions that are possible at each carbon cost (the ends of each curve correspond to $0 and $200/tCO₂ carbon costs).

The addition of uniformly charged PHEVs sharply reduces the emissions at each carbon cost, and also allows a slight reduction in average power prices, as the load factor of the system is increased and more low-cost resources are added to the portfolio to meet the additional demand. This step would also save significant costs that are not shown on this chart: vehicle owners charging at power costs of $70–80/MWh would pay only about $1.25 per gallon of gasoline they displaced.²⁶ On the other hand, the cost of generating power from natural gas could rise in this scenario, as supplies become more constrained – a factor not included in my analysis.

Charging PHEVs at optimal times instead of around-the-clock would not have much effect on the emission savings available at any particular carbon cost level. How-

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²⁶ $70/MWh x 1 MWh/3600 MJ x 131 MJ / gallon gasoline x 0.25 gasoline vehicle efficiency / 0.8 electric vehicle efficiency x 1.0725 California sales tax + $0.18/gal California excise tax + $0.184/gal Federal excise tax = $1.22/gallon gasoline equivalent.
ever, it could reduce the average cost of power at all carbon cost levels, as the optimal system design includes fewer gas plants, uses less solar power and relies more heavily on low-cost wind power.

Beyond this point, reducing traditional electricity loads (and introducing some demand elasticity) yields some additional savings in both carbon dioxide emissions and power costs.

9.3 Composition of the Lowest-Emissions Power System

Figures 52 and 53 show the generators selected for the lowest-cost power system at the $200/t\text{CO}_2$ carbon cost, in the most pro-renewables scenario discussed above — more wind sites, optimally charged PHEVs and 20 percent load reductions by 2022. This system design that yields the lowest greenhouse gas emissions of all scenarios considered in this dissertation. In this scenario, the least-cost option is to build about 29 GW of wind plants in the first investment period, and continue adding wind capacity as the vehicle load rises and existing plants are retired. The optimal investment plan also includes 14–20 GW of solar troughs in the later investment periods. Distributed photovoltaic systems serve a relatively minor role in this scenario, amounting to 71 MW by 2022. Existing coal plants are also shut down, due to the high cost of carbon dioxide emissions.
By the final investment period, in this scenario, the power system obtains 84 percent of its electricity from fossil-free sources; this electricity provides power for traditional loads at roughly today’s level, and also provides an average of 10.5 GW for vehicle
charging, enough to displace at least half of the state’s gasoline use. The total emissions in the final investment period are 17.5 million tCO₂/year, which, as noted above, is 88 percent lower than the 1990 level for the same services.

The average cost of electricity in this system is $80.50/MWh, net of the cost of carbon dioxide emissions. This cost is lower than the $200/tCO₂ version of the base-case model (the upper end of the black curve in Figure 51), and actually falls only 5 percent above the $0/tCO₂ version of the base-case model (the lower end of the black curve in Figure 51). This suggests that a high-renewables scenario with strong emphasis on energy efficiency and intelligently charged electric vehicles could yield radical emission reductions at a cost barely above the lowest possible cost that might otherwise be expected.

9.4 Operation of the Lowest-Emissions Power System

For further reference, Figure 54 shows how the Switch model dispatches generators and loads on the peak load days during the final study period. In this figure, power output from each type of generator is shown in stacked bands. Thin lines show the “fixed” system load for electricity (red line), the electricity used in addition to this for hydro pumping (darker blue line), and the additional electricity used for vehicle charging (black line at the top of the figure). Baseload plants, gas generators, solar and wind facilities are combined to provide power output that roughly corresponds to the traditional electric loads (red line). Then vehicles are charged using additional power produced beyond this level, primarily at night. In this example, the system often uses hydropower to charge these vehicles, and the model picks hours fairly idiosyncratically for this process, since it has no reason to prefer any particular hour over any other. This system would likely have enough flexibility to charge these vehicles during more customer-preferred times.
Although this scenario uses rather simplistic assumptions, it does suggest that there is potential for achieving sharp emission reductions by combining energy efficiency, strong development of renewable power sources, electric vehicles and demand-side flexibility. Prices of batteries for electric vehicles may need to fall below current levels to make this strategy completely cost-effective (Lemoine et al. 2008), and the costs of wind and solar equipment must also continue to decline as they have historically. It may also be necessary to send price signals to vehicles on a shorter-than-hourly basis, so they can respond to short-term variations in the supply of power. However, no other major technical breakthroughs or infrastructure development are needed to make this scenario a reality.
CHAPTER 10: CONCLUSIONS

The first half of this thesis focused on the design of the Switch model, a new tool for identifying the optimal set of investments in the power system over a multi-decade period, under any given set of assumptions about the value of avoiding carbon dioxide emissions and the future cost of conventional and renewable generators, fuels and transmission capacity.

One use of this model is to develop “supply curves,” showing total the amount of carbon dioxide emissions that can be avoided at or below any particular cost per ton. I discussed how these curves can be used to develop harmonized emission-reduction targets for each sector of the economy, in order to achieve statewide emission reductions at the lowest possible cost. I also found that even if no value is placed on reducing carbon dioxide emissions (i.e. a $0/tCO₂ cost is assigned to emissions), the least-expensive option for California would be to obtain about 18 percent of its power from wind farms by 2022, reducing emissions by 14 percent relative to 1990. I further found that a 33% renewable portfolio standard by 2022 would correspond to a marginal cost of emission reductions around $60/tCO₂. Both of these are conservative estimates; the optimal portfolios would likely include much more wind power if more sites were considered than the ones for which I happen to have data.

I also used the Switch model to chart how the average cost of electricity might change as the system is redesigned to achieve lower emission levels. I found that the cost of electricity rises surprisingly gradually as renewable resources are used for more of the system load, and that there appears to be no sharp limit to the share of energy that could be provided by renewable resources. If no value is given to avoiding greenhouse gas emissions, the least expensive investment plan would have emissions 14 percent below the
1990 level by 2022–25, with average power costs of $80/MWh. On the other hand, if we assign a cost of $200/tCO₂, we would want to develop a system that reduces emissions by 65 percent below 1990 levels by 2022. This system would have an average power cost of $94/MWh in 2022–25, not quite 20 percent more than the least expensive system possible.

Most of the optimal investment plans discussed here use some but not all of the wind and solar capacity that could potentially be developed in California. This raises the question of why we would want to halt the development of wind or solar resources at any particular level. I found that wind or solar facilities can provide two main types of benefit to the power system: a capacity benefit, when they allow us to avoid building conventional power plants to meet peak loads; and an energy benefit, when they allow us to avoid the costs of fuel and greenhouse gas emissions from fossil plants. Both of these benefits decrease as the size of the renewable portfolio increases. When the incremental benefit eventually drops below the cost of additional wind or solar power, it becomes uneconomical to expand these resources further.

Much attention has been paid to the small and declining capacity benefit from renewable resources. But I find that with high fuel costs or a strong interest in reducing greenhouse gas emissions, this is not likely to be the main factor limiting the use of renewable power – it may be worthwhile to develop these resources even if they must be backed up by little-used conventional power plants. However, the decrease in energy benefits could impose a more fundamental limit on the use of renewable resources. As the number of wind or solar plants is expanded, eventually a point is reached where additional plants will provide power during many hours when loads are already satisfied by the previously built plants. Beyond this point, an increasing share of the energy from addi-
tional wind or solar plants will be discarded as surplus. This directly reduces the energy benefits from these plants, so that eventually investment must stop, no matter how high the cost of carbon dioxide emissions or how inexpensive these plants are.

I next investigated whether the power system would be able to use a greater share of resources from a diversified portfolio of wind and solar sites than it could if only one technology – or even one project site – were available. I found that if wind were the only renewable resource to be added, then aggregating widely dispersed wind farms might not make much difference, at least within the limits of my analysis: the system appears to be able to use nearly all of the available wind capacity, whether it is spatially diversified or not. If we consider only solar sites, then spatial diversification does moderately increase the amount that can be used. However, I found that the biggest benefit comes from combining both wind and solar sites – wind and solar power are available at complementary times in California, so the system is able to use about 50 percent more of the two resources together than it could of either alone.

I finished my analysis by considering a scenario where several of the constraints on the use of renewable energy are relaxed: I assumed that twice as much wind capacity could be developed (still only 20 percent of California’s gross wind potential), that energy efficiency measures restrained electricity demand at 2010 levels, that plug-in hybrid-electric vehicles could be used to displace half of the state’s gasoline use, and that these vehicles were charged at optimally chosen times. In this not-entirely-unrealistic scenario, I found that California’s greenhouse gas emissions could be reduced radically at modest cost – as much as 88 percent below 1990 levels, while keeping average power costs within 5 percent of the base-case, no-carbon-cost level.
This dissertation provides an optimistic new view of the role that intermittent renewable resources could play in the power system. I have attempted to keep my assumptions as conservative as possible and the workings of the model as transparent as possible, so these findings spring more or less directly from the forecasts of falling prices for renewable energy and sustained high costs for fossil fuels. Some concerns may linger remain about the modeling approach. The Switch model considers the performance of renewable resources during more hours than any previous power production cost optimization model, but the portfolios it proposes have not yet been tested against the full range of conditions the power system may encounter. I have also overlooked important questions about how sub-hourly variations in the supply of power can be smoothed over in a power system that uses much more renewables and less dispatchable capacity than we ever have in the past. On the other hand, my main analysis cases leave out some factors that may improve the outlook for renewable resources, such as the development of more storage capacity, and the identification of a more complete set of potential wind farm sites.

In this research, I have principally discussed what components should be included in the power system in order to provide power at the lowest cost for all customers. However, I have not discussed how we could ensure that these elements are added to the power system. The California power system is an extraordinarily complex entity, with a mixture of public and private control areas, market-based and regulated transactions. It is not clear that the existing system will develop an optimal mix, even if a carbon tax or cap-and-trade system is imposed. The results of analysis like these can help to point the way to the least-expensive response to climate change in the electric system, but con-
certain action will be needed by all the participants to develop such a system. Some key areas of focus could include

- ensuring that the cost of renewable technology continues to fall as forecast here;
- arranging low-cost financing and secure revenues for renewable-power facilities;
- developing markets for energy services that can smooth over the variation in renewable power supplies at a fair price; and
- developing an open and effective process for weighing the land-use impacts of wind and solar facilities and transmission lines against their climate change benefits.
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Appendix

This Appendix includes a complete copy of the Switch model, as implemented in the AMPL optimization program. It also includes examples of the data tables used to initialize the model and copies of the scripts used to export the model’s results.

A.1 Core Model

The scripts described in this section – windsun.mod and windsun.run – constitute the core of the Switch model.

A.1.1 windsun.mod

This is the main definition for the model. It and all associated data are loaded by windsun.run.

```
windsun.mod

# Time-tracking parameters

set YEARS ordered; # all possible years
set HOURS ordered;

# each hour is assigned to a study period exogenously,
# so that we don't have to do any arithmetic to figure out
# which hour is in each period. This allows for arbitrary
# numbering of the hours, so they need not be spaced integral
# number of hours apart through the whole year. This is important
# if we want to sample, e.g., 12*24 hours per year or per 3 years.
# Another way to do it would be to exogenously specify
# how many samples there are per study period, and then bundle
# them up within the model. That would allow us to change the length
# of the study period from inside the model.
# But it wouldn't gain us very much, since the sampling must be
# done carefully for each study period anyway.
```
# chronological information on each study hour (sample)
# this is used to identify which hours fall in each study period
# and how many real hours are represented by each sample (which may be fractional).
# Hour_of_day and month_of_year are just used for reporting (if that)
param period {HOURS};
param date {HOURS};
param hours_in_sample {HOURS};
param month_of_year {HOURS};
param season_of_year {h in HOURS} = floor((month_of_year[h]-1)/3)+1;

# note: periods must be evenly spaced and count by years,
# but they can have decimals (e.g., 2006.5 for July 1, 2006)
# and be any distance apart.
# VINTAGE_YEARS are a synonym for PERIODS, but refer more explicitly
# the date when a power plant starts running.
set PERIODS ordered = setof {h  in HOURS} (period[h]);
set VINTAGE_YEARS ordered = PERIODS;

# specific dates are used to collect hours that are part of the same
# day, for the purpose of hydro dispatch, etc.
set DATES ordered = setof {h in HOURS} (date[h]);

set HOURS_OF_DAY ordered = setof {h in HOURS} (hour_of_day[h]);
set MONTHS_OF_YEAR ordered = setof {h in HOURS} (month_of_year[h]);
set SEASONS_OF_YEAR ordered = setof {h in HOURS} (season_of_year[h]);

# make sure every HOUR_OF_DAY is modeled on every date
# (this could be relaxed later, but is currently assumed true for the daily constraint on simple hydro dispatch)
check card(HOURS_OF_DAY) * card(DATES) = card(HOURS);

# the date (year and fraction) when the optimization starts
param start_year = first(PERIODS);

# interval between study periods
# this is calculated from the study period intervals if possible,
# otherwise it's assumed to be just a one-year study
param years_per_period >= 0
  default if last(PERIODS) = first(PERIODS) then 1 else (last(PERIODS)-first(PERIODS))/(card(PERIODS)-1);

# the first year that is beyond the simulation
# (i.e., this would be the first year of the next simulation, if there were one)
param end_year = last(PERIODS)+years_per_period;

# list of all load zones in the state
# it is ordered, so they are listed from north to south
set LOAD_ZONES ordered;

windsun.mod
# base-case system load (MWa):
# part is fixed to happen during a particular hour,
# part can be moved to any hour of the day
# NOTE: if an annual electricity demand curve is provided,
# the fixed portion of load will be adjusted up or down from this level
param system_load_fixed {LOAD_ZONES, HOURS} >= 0;
param system_load_moveable {LOAD_ZONES, DATES} >= 0 default 0;

# peak system-wide load during each study period
param system_load_peak {p in PERIODS}
  = max {h in HOURS: period[h]=p} sum {z in LOAD_ZONES} system_load_fixed[z, h];

# planning reserve margin - fractional extra load the system must be able able to serve
# when there are no forced outages
param planning_reserve_margin >= 0;

##############################################
#
# Piecewise supply curves for two types of demand response or efficiency:
# - "interruptible load" can be turned off during critical peak hours, in exchange for some payment.
# - "annual demand" scales the loads in each zone up or down depending on the price of power
# The cost of interruptible load would most likely be paid out as part of a capacity auction.
# The annual demand curve indicates the benefit of providing power to customers.
# It could also be interpreted as the cost of energy efficiency projects that save power and
# leave the customers just as well off as they were to begin with. Or it could be the amount that
# some customers would have to be paid to reduce their year-round consumption (maybe that would
# have to be the difference between the cost of producing power and the benefit of using it.)
# Note that this formulation allows demand reduction to be included in one study period and
# left unused in the next one; there is currently no treatment of sunk costs (e.g., for efficiency projects).
#
# interruptible load (IL) reduces the need for reserve margins, but has no effect on normal dispatch
# (mostly because I can't think of a way to get the interruptible load to be dispatched after everything else,
# without also changing how much of it gets built. i.e., if I use a high dispatch cost, we will be less inclined
# to build it. the only other way is some sort of "if" constraint: if reserve margin can be met without interruptible
# load, then do so; otherwise, dispatch enough interruptible load to keep reserves up [which may also reduce loads])
#
# TODO: change interruptible load formulation to use an exogenously specified supply curve,
# like annual demand, and eliminate the other parameters.
#
# elasticity of interruptible load
# this is the amount (in dollars per kw-year) by which the cost of
# interruptible load increases for each percent of the system peak load
# that is satisfied with interruptible load
param interruptible_load_cost_per_kw_year_per_percent_peak_load >= 0 default 0;

# the maximum amount of interruptible load that can be used in any load zone
# (specified as a fraction of the peak load, e.g., 0.20)
param interruptible_load_max_share >= 0 default 0;

# the total cost of developing interruptible load is quadratic in the
# amount developed, but we approximate it using a piecewise-linear curve.
# this tells how many segments are in that curve
param interruptible_load_cost_segment_count >= 0 default 5;
# Points along a stepwise demand curve for electricity (on an annual time scale).
# The first and last breakpoints show the minimum and maximum possible
# annual demand (as a fraction of base-case year round power consumption in each zone).
# Between those is shown the power price that would induce each level of demand
# (or, equivalently, the benefit delivered [to customers] by generating additional power
# when the total supply is at each level).
# The power prices are expressed as fractions of a base-case price in each zone.
# The price levels are assumed to apply at or above each breakpoint.
# The last price level is never used, because it is above the highest allowed load.
# To use a fixed power demand instead of a supply curve, just use the default values
# (one breakpoint with a quantity and price of 1).

set ANNUAL_DEMAND_BREAKPOINTS ordered default {1};
param annual_demand_quantity_vs_base {ANNUAL_DEMAND_BREAKPOINTS} >= 0 default 1;
param annual_demand_price_vs_base {ANNUAL_DEMANDBREAKPOINTS} default 1;
# demand curve must be strictly non-increasing
# (if it dropped and rose, that would create local maxima in the total benefit curve)
check {bp in ANNUAL_DEMAND_BREAKPOINTS: ord(bp) > 1}:
   annual_demand_quantity_vs_base[bp] >= annual_demand_quantity_vs_base[prev(bp)];
check {bp in ANNUAL_DEMAND_BREAKPOINTS: ord(bp) > 1}:
   annual_demand_price_vs_base[bp] <= annual_demand_price_vs_base[prev(bp)];

# base-case marginal cost or value of year-round power
# this could be specified differently for each period, but for now,
# we use a single value for each zone, and just read it from the .dat file.
param annual_demand_price_base {LOAD_ZONES} >= 0 default 0;

# note: base-case electricity demand is specified by system_load_fixed
# TODO: rename system_load_fixed to fit better with the supply curve paradigm

# note: “base-case” and “base” in the power demand curves refer to the single known
# price/quantity point on the curve, i.e., the power consumption forecasted for some future
# period and the marginal benefit of supplying that power, or the marginal price used for that forecast.
# The base-case consumption is usually provided by some state agency, and the base-case benefit
# can be found by running this model in a way consistent with that forecast, with demand curve
# constrained to be vertical, and then reading out the dual values of the vertical constraint on the
# demand curve (i.e., the marginal cost of providing that power).
# e.g., if the forecaster says they assumed future costs would be the same as the past, you can
# get the historical marginal cost of power by running the model for an historical year.
# (see load_historical_year.run, then you can use this command to get suitable costs to put in windsun.dat:
# display {z in LOAD_ZONES} Minimum_Maximum_Annual_Demand{z, first(PERIODS)}/
# annual_cost_weight[first(PERIODS)];
# These costs may not match the customer prices used by the forecaster,
# but they should have the same relationship to those prices as future marginal costs have to
# future prices faced by electricity customers (at least as a first guess).
# At any rate, “base-case” and “base” do not refer to a base-case future scenario or to
# baseload power production; they only refer to the single, known price/quantity point
# on the demand curve.

# Technology specifications
# (most of these come from generator_costs.dat or windsun.dat)
# list of all available technologies (from the generator cost table)
set TECHNOLOGIES;

# list of all possible fuels
set FUELS;

# year for which the price of each technology has been specified
param price_year {TECHNOLOGIES} >= 0;

# earliest time when each technology can be built
param min_vintage_year {TECHNOLOGIES} >= 0;

# overnight cost for the plant ($/kW)
param overnight_cost {TECHNOLOGIES} >= 0;

# cost of grid upgrades to deliver power from the new plant to the “center” of the load zone
# (specified generically for all projects of a given technology, also specified per-project below.
# if specified in both places, the two will be summed; usually one of them will be zero.)
param connect_cost_per_kw_generic {TECHNOLOGIES} >= 0;

# fixed O&M ($/kW-year)
param fixed_o_m {TECHNOLOGIES} >= 0;

# variable O&M ($/MWh)
param variable_o_m {TECHNOLOGIES} >= 0;

# annual rate of change of overnight cost, beginning at min_vintage_year
param overnight_cost_change {TECHNOLOGIES};

# annual rate of change of fixed O&M, beginning at min_vintage_year
param fixed_o_m_change {TECHNOLOGIES};

# fuel used by this type of plant
param fuel {TECHNOLOGIES} symbolic in FUELS;

# heat rate (in Btu/kWh)
param heat_rate {TECHNOLOGIES} >= 0;

# construction lead time (years)
param construction_time_years {TECHNOLOGIES} >= 0;

# life of the plant (age when it must be retired)
param max_age_years {TECHNOLOGIES} >= 0;

# fraction of the time when a plant will be unexpectedly unavailable
param forced_outage_rate {TECHNOLOGIES} >= 0, <= 1;

# fraction of the time when a plant must be taken off-line for maintenance
param scheduled_outage_rate {TECHNOLOGIES} >= 0, <= 1;

# does the generator have a fixed hourly capacity factor?
param intermittent {TECHNOLOGIES} binary;
# can this type of project only be installed in limited amounts?
param resource_limited {TECHNOLOGIES} binary;

# Project data

# default values for projects that don't have sites or orientations
param site_unspecified symbolic;
param orient_unspecified symbolic;

# Names of technologies that have capacity factors or maximum capacities
# tied to specific locations.
param tech_pv symbolic in TECHNOLOGIES;
param tech_trough symbolic in TECHNOLOGIES;
param tech_wind symbolic in TECHNOLOGIES;

# names of other technologies, just to have them around
# (but this is getting silly)
param tech_ccgt symbolic in TECHNOLOGIES;
param tech_ct symbolic in TECHNOLOGIES;

# maximum capacity factors (%) for each project, each hour.
# generally based on renewable resources available
set PROJ_INTERMITTENT_HOURS dimen 5; # LOAD_ZONES, TECHNOLOGIES, SITES, ORIENTATIONS, HOURS
param cap_factor {PROJ_INTERMITTENT_HOURS} >= 0, <= 1;
set PROJ_INTERMITTENT = setof {(z, t, s, o, h) in PROJ_INTERMITTENT_HOURS} (z, t, s, o);
# make sure all hours are represented
check {(z, t, s, o) in PROJ_INTERMITTENT, h in HOURS}: cap_factor[z, t, s, o, h] >= 0;
check {(z, t, s, o) in PROJ_INTERMITTENT}: intermittent[t];

# maximum capacity (MW) that can be installed in each project
set PROJ_RESOURCE_LIMITED dimen 4; # LOAD_ZONES, TECHNOLOGIES, SITES, ORIENTATIONS
param max_capacity {PROJ_RESOURCE_LIMITED} >= 0;
check {(z, t, s, o) in PROJ_RESOURCE_LIMITED}: resource_limited[t];

# all other types of project (dispatchable and installable anywhere)
set PROJ_ANYWHERE = LOAD_ZONES cross
    setof {t in TECHNOLOGIES: not intermittent[t] and not resource_limited[t]}
        (t, site_unspecified, orient_unspecified);

# some projects could be resource-limited but not intermittent (e.g., geothermal).
# solar troughs are intermittent but not resource limited
# so we union all the possibilities
set PROJECTS = PROJ_ANYWHERE
union PROJ_INTERMITTENT
union PROJ_RESOURCE_LIMITED;

# the set of all dispatchable projects (i.e., non-intermittent)
set PROJ_DISPATCH = (PROJECTS diff PROJ_INTERMITTENT);
# sets derived from site-specific tables, help keep projects distinct
set SITES = setof {(z, t, s, o) in PROJECTS} (s);
set ORIENTATIONS = setof {(z, t, s, o) in PROJECTS} (o);

# distance to connect a new project to an interconnect point on the grid, in km.
# a line of this length will need to be built, at the standard transmission line cost.
param connect_length_km {(z, t, s, o) in PROJECTS} >= 0 default 0;

# cost of grid upgrades to support a new project, in dollars per peak kW.
# these are needed in order to deliver power from the interconnect point to
# the load center (or make it deliverable to other zones)
param connect_cost_per_kw {(z, t, s, o) in PROJECTS} >= 0 default 0;

# Existing hydro plants (assumed impossible to build more, but these last forever)

# forced outage rate for hydroelectric dams
# this is used to de-rate the planned power production
param forced_outage_rate_hydro >= 0;

# round-trip efficiency for storing power via a pumped hydro system
param pumped_hydro_efficiency >= 0;

# annual cost for existing hydro plants (see notes in windsun.dat)
# it would be better to calculate this from the capital cost, fixed and variable O&M,
# but that introduces messy new parameters and doesn't add anything to the analysis
param hydro_annual_payment_per_mw >= 0;

# indexing sets for hydro data (read in along with data tables)
# (this should probably be monthly data, but this has equivalent effect,
# and doesn't require adding a month dataset and month <-> date links)
set PROJ_HYDRO_DATES dimen 3; # load_zone, site, date

# minimum, maximum and average flow (in average MW) at each dam, each day
# (note: we assume that the average dispatch for each day must come out at this average level,
# and flow will always be between minimum and maximum levels)
# maximum is based on plant size
# average is based on historical power production for each month
# for simple hydro, minimum flow is a fixed fraction of average flow (for now)
# for pumped hydro, minimum flow is a negative value, showing the maximum pumping rate
param avg_hydro_flow {PROJ_HYDRO_DATES};
param max_hydro_flow {PROJ_HYDRO_DATES};
param min_hydro_flow {PROJ_HYDRO_DATES};
check {(z, s, d) in PROJ_HYDRO_DATES}:
  min_hydro_flow[z, s, d] <= avg_hydro_flow[z, s, d] <= max_hydro_flow[z, s, d];

# list of all hydroelectric projects (pumped or simple)
set PROJ_HYDRO = setof {(z, s, d) in PROJ_HYDRO_DATES} (z, s);
# pumped hydro projects (have negative minimum flows at some point),
# or any projects that should get individual-hour dispatch
# set PROJ_PUMPED_HYDRO = setof {{z, s, d} in PROJ_HYDRO_DATES} (z, s);
# the next two limits are equivalent (they give individual dispatch of all large hydro, and aggregated dispatch of small, baseload hydro)
# set PROJ_PUMPED_HYDRO = setof {{z, s, d} in PROJ_HYDRO_DATES: min_hydro_flow[z, s, d] < 0 or z="Northwest" or max_hydro_flow[z, s, d] >= 50} (z, s);
# set PROJ_PUMPED_HYDRO = setof {{z, s, d} in PROJ_HYDRO_DATES: min_hydro_flow[z, s, d] < 0.9999 * avg_hydro_flow[z, s, d]} (z, s);
set PROJ_PUMPED_HYDRO = setof {{z, s, d} in PROJ_HYDRO_DATES: min_hydro_flow[z, s, d] < 0 or z="Northwest" or max_hydro_flow[z, s, d] >= 100} (z, s);
# set PROJ_PUMPED_HYDRO = setof {{z, s, d} in PROJ_HYDRO_DATES: min_hydro_flow[z, s, d] < 0 or z="Northwest"} (z, s);
# model can fit in 32-bit cplex with installtrans fixed, or with individual dispatch only for hydro sites >= 100 MW.
# it cannot fit if installtrans is free and sites between 50 and 100 MW are dispatched individually.

# simple hydro projects (everything else)
set PROJ_SIMPLE_HYDRO = PROJ_HYDRO diff PROJ_PUMPED_HYDRO;

# make sure the data tables have full, matching sets of data
check card(DATES symdiff setof {{z, s, d} in PROJ_HYDRO_DATES} (d)) = 0;
check card(PROJ_HYDRO_DATES) = card(PROJ_HYDRO) * card(DATES);

# simple hydro projects are dispatched on a linearized, aggregated basis in each zone
# the code below sets up parameters for this.

# maximum share of each day's "discretionary" hydro flow
# (everything between the minimum_hydro_flow and the average_hydro_flow)
# that can be dispatched in a single hour.
# Higher values will produce narrower, taller hydro dispatch schedules,
# but also more "baseload" hydro.

# TODO: convert discretionary hydro dispatch DispatchHydroShare[] and DispatchHydroShare_Reserve[]
# to be a flow rate in MW, whose sum is limited to (# samples per day) * (avg flow - min flow).
# In each hour, it would be limited to max_multiple_of_avg_discretionary_rate * (avg flow - min flow)
# (instead of [# samples per day] * [an arbitrary fraction of 1]).
# This will avoid having to sum (arbitrarily) to 1 and then multiply each hour's number by 24 * (avg - min),
# and will avoid putting the (# samples per day) in the hourly flow constraint.
# (wait till next time a full set of solutions is run, to avoid interfering with older saved solutions)
# MAYBE better than that: stick with percentages, but have them be percentages of the average discretionary
# flow rate, with a requirement that the average across all hours (instead of sum) is 1.

param max_hydro_dispatch_per_hour;
param min_hydro_dispatch {{z, s} in PROJ_SIMPLE_HYDRO, d in DATES} =
    max(
        # if the avg_hydro_flow is close to the max_hydro_flow for this site, then we need to increase the
        # minimum flow rate, reducing the amount of "discretionary" hydro, so that when max_hydro_dispatch_per_hour
        # is dispatched, it won't overshoot the max_hydro_flow for this site.
        # note: this term is just the solution to the reqmt that min + max_per_hour * 24 * (avg - min) <= max
        (max_hydro_dispatch_per_hour * 24 * avg_hydro_flow[z, s, d] - max_hydro_flow[z, s, d])
    / (max_hydro_dispatch_per_hour * 24 - 1),
    min_hydro_flow[z, s, d];

# make sure we'll never overshoot maximum allowed production
check {{z, s} in PROJ_SIMPLE_HYDRO, d in DATES}:
    min_hydro_dispatch[z, s, d]
    + max_hydro_dispatch_per_hour * (avg_hydro_flow[z, s, d] - min_hydro_dispatch[z, s, d]) * 24
    <= max_hydro_flow[z, s, d] * 1.001;

# pre-aggregate the available simple hydro supply for use in the satisfy_load constraint
param min_hydro_dispatch_all_sites {z in LOAD_ZONES, d in DATES} = sum {{z, s} in PROJ_SIMPLE_HYDRO} min_hydro_dispatch[z, s, d];
param avg_hydro_dispatch_all_sites {z in LOAD_ZONES, d in DATES} = sum {{z, s} in PROJ_SIMPLE_HYDRO} avg_hydro_flow[z, s, d];

# name of each plant
set EXISTING_PLANTS dimen 2;  # load zone, plant code
check {z in setof {{z, e} in EXISTING_PLANTS} (z)}: z in LOAD_ZONES;

# the size of the plant in MW
param ep_size_mw {EXISTING_PLANTS} >= 0;

# NOTE: most of the remaining per-plant data could be
# stored on an aggregated basis in the generator_cost table,
# and then each plant could just specify a load zone and technology.
# However, individual plants would probably still need a custom
# heat rate, and maybe forced outage rate,
# which would override the generic technology specification.

# type of fuel used by the plant
param ep_fuel {EXISTING_PLANTS} symbolic in FUELS;

# heat rate (in Btu/kWh)
param ep_heat_rate{EXISTING_PLANTS} >= 0;
# year when the plant was built (used to calculate annual capital cost and retirement date)
param ep_vintage {EXISTING_PLANTS} >= 0;

# life of the plant (age when it must be retired)
param ep_max_age_years {EXISTING_PLANTS} >= 0;

# overnight cost of the plant ($/kW)
param ep_overnight_cost {EXISTING_PLANTS} >= 0;

# fixed O&M ($/kW-year)
param ep_fixed_o_m {EXISTING_PLANTS} >= 0;

# variable O&M ($/MWh)
param ep_variable_o_m {EXISTING_PLANTS} >= 0;

# fraction of the time when a plant will be unexpectedly unavailable
param ep_forced_outage_rate {EXISTING_PLANTS} >= 0, <= 1;

# fraction of the time when a plant must be taken off-line for maintenance
# note: this is also used for plants that only run part time
# e.g., a baseload-type plant with 97% reliability but 80% capacity factor
param ep_scheduled_outage_rate {EXISTING_PLANTS} >= 0, <= 1;

# does the generator run at its full capacity all year?
param ep_baseload {EXISTING_PLANTS} binary;

# is the generator part of a cogen facility (used for reporting)?
param ep_cogen {EXISTING_PLANTS} binary;

#########################################################
# Transmission lines

# cost to build a transmission line, per mw of capacity, per km of distance
# (assumed linear and can be added in small increments!)
param transmission_cost_per_mw_km >= 0;

# retirement age for transmission lines
param transmission_max_age_years >= 0;

# forced outage rate for transmission lines, used for probabilistic dispatch(!)
param transmission_forced_outage_rate >= 0;

# x and y coordinates of center of each load zone, in meters
param load_zone_x {LOAD_ZONES};
param load_zone_y {LOAD_ZONES};

# possible transmission lines are listed in advance;
# these include all possible combinations of load_zones, with no double-counting
# The model could be simplified by only allowing lines to be built between neighboring zones.
set TRANS_LINES in {LOAD_ZONES, LOAD_ZONES};

# length of each transmission line
param transmission_length_km {TRANS_LINES};
# delivery efficiency on each transmission line
param transmission_efficiency {TRANS_LINES};

# the rating of existing lines in MW (can be different for the two directions)
param existing_transmission_from {TRANS_LINES} >= 0 default 0;
param existing_transmission_to {TRANS_LINES} >= 0 default 0;

# unique ID for each transmission line, used for reporting results
param tid {TRANS_LINES};

# parameters for local transmission and distribution from the large-scale network to distributed loads
param local_td_max_age_years >= 0;
param local_td_annual_payment_per_mw >= 0;

#############################
#
# Financial data and calculations
#
# the year to which all costs should be discounted
param base_year >= 0;

# annual rate (real) to use to discount future costs to current year
param discount_rate;

# discount factor to use for each study period
param discount_factor {p in PERIODS} = 1 / (1 + discount_rate)^(p - base_year);

# required rates of return (real) for generator and transmission investments
# may differ between generator types, and between generators and transmission lines
param finance_rate {TECHNOLOGIES} >= 0;
param transmission_finance_rate >= 0;

# cost of carbon emissions ($/ton), e.g., from a carbon tax
# can also be set negative to drive renewables out of the system
param carbon_cost;

# annual fuel price forecast
param fuel_cost {YEARS, FUELS} default 0, >= 0;
# this defaults to zero (for renewables), but we need to make sure
# that if a non-zero values are given for any year, they are given for all years
check {y in YEARS, f in setof {y1 in YEARS, f1 in FUELS: fuel_cost[y1, f1] > 0} (f1)}: fuel_cost[y, f] > 0;

# carbon content (tons) per million Btu of each fuel
param carbon_content {FUELS} default 0, >= 0;

# Calculate discounted fixed and variable costs for each technology and vintage
# For now, all hours in each study period use the fuel cost
# from the year when each study period started.
# This is because we don't want artificially strong run-ups in fuel prices
# between the beginning and end of each study period as a result of the long intervals
# needed to make it solvable.
# This could be updated to use fuel costs that vary by month,
# or for an hourly model, it could interpolate between annual forecasts
# (see versions of this model from before 11/27/07 for code to do that).
param fuel_cost_hourly {f in FUELS, h in HOURS} := fuel_cost[floor(period[h]), f];

# weighting factors for annual and hourly costs.
# These account for the number of hours represented by each sample,
# or number of years during each study period. They also discount costs
# that are spread across each study period up to the start of the study
# period. Finally, they discount from the start of each study period
# to the base year.
param annual_cost_weight {p in PERIODS} =
  (1-(1/(1+discount_rate)^(years_per_period)))/discount_rate
  * 1 / (1 + discount_rate)^(p - base_year);

param hourly_cost_weight {h in HOURS} =
  hours_in_sample[h]
  * 1 / (1 + discount_rate)^(period[h] - base_year);
  
# TODO: better to define it as below, once the first way has been compared to the original approach
# the second way (below) accounts for the fact that we assume the hourly costs are
# incurred repeatedly during all the years of the study period, rather than all at the start.
# If this is changed, it will also need to be changed in record_results.run and the sensitivity analysis scripts.
# (probably better to wait for a full overhaul of how discounting is done -- break up the objective function
# into pieces -- direct costs for each major category, each period, then discount them as they are combined into one
# cost.
# then those pieces can be used easily for various kinds of reporting (e.g., undiscounted cost per year in final study
# period.
# or tons of CO2/year in final study period))
#param hourly_cost_weight {h in HOURS} =
#  = annual_cost_weight[period[h]] * hours_in_sample[h]/years_per_period[period[h]];

# TODO: convert discounted cost terms below to use the annual_cost_weight and hourly_cost_weight,
# (maybe change fixed_cost into fixed_cost_discounted)
# and, ideally, move the discounting all the way into the objective function
# This will help with adding an extra "steady state" period at the end with a different weight
# (to account for residual value at end of scenario)

##########
# calculate discounted costs for new plants

# apply projected annual real cost changes to each technology,
# to get the capital, fixed and variable costs if it is installed
# at each possible vintage date
param capital_cost_proj {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS} = 
    overnight_cost[t] * (1+overnight_cost_change[t])^(v-min_vintage_year[t]) 
    + connect_length_km[z, t, s, o]  * transmission_cost_per_mw_km / 1000 
    + connect_cost_per_kw_generic[t] 
    + connect_cost_per_kw[z, t, s, o];

param fixed_cost_proj {t in TECHNOLOGIES, v in VINTAGE_YEARS} = 
    fixed_o_m[t] * (1+fixed_o_m_change[t])^(v-min_vintage_year[t]);

# annual revenue that will be needed to cover the capital cost
param capital_cost_annual_payment {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS} = 
    finance_rate[t] * (1 + 1/(1+finance_rate[t])^(max_age_years[t]-1)) * capital_cost_proj[z, t, s, o, v];

# date when a plant of each type and vintage will stop being included in the simulation
# note: if it would be expected to retire between study periods,
# it is kept running (and annual payments continue to be made)
# until the end of that period. This avoids having artificial gaps
# between retirements and starting new plants.
param project_end_year {t in TECHNOLOGIES, v in VINTAGE_YEARS} = 
    min(end_year, v+ceil(max_age_years[t]/years_per_period)*years_per_period);

# finally, take the stream of fixed costs over the duration of the project,
# and discount to a lump-sum value at the start of the project,
# then discount from there to the base_year.
# Reported costs are in $/kW, but we need $/MW, so we multiply by 1000.
param fixed_cost {t in TECHNOLOGIES, h in HOURS} = 
    (capital_cost_annual_payment[z,t,s,o,v] + fixed_cost_proj[t,v]) * 1000 
    * (1-(1/(1+discount_rate)^(project_end_year[t,v]-v)))/discount_rate 
    * discount_factor[v];

param variable_cost {t in TECHNOLOGIES, h in HOURS} = 
    hours_in_sample[h] * ( 
        variable_o_m[t] 
        + heat_rate[t]/1000 * fuel_cost_hourly[fuel[t], h] 
    ) * discount_factor[period[h]];
param carbon_cost_per_mwh {t in TECHNOLOGIES, h in HOURS} =
    hours_in_sample[h] * (
        heat_rate[t]/1000 * carbon_content[fuel[t]] * carbon_cost
    ) * discount_factor[period[h]];

########
# now get discounted costs for existing projects on similar terms

# year when the plant will be retired
# this is rounded up to the end of the study period when the retirement would occur,
# so power is generated and capital & O&M payments are made until the end of that period.
# note: this is set as a default value rather than a direct assignment, so that it can be changed
# if plants need to be forced not to retire.
param ep_end_year {(z, e) in EXISTING_PLANTS} default
    min(end_year, start_year+ceil((ep_vintage[z, e]+ep_max_age_years[z, e]-
        start_year)/years_per_period)*years_per_period);

# annual revenue that is needed to cover the capital cost (per kw)
# TODO: find a better way to specify the finance rate applied to existing projects
# for now, we just assume it's the same as a new CCGT plant
param ep_capital_cost_annual_payment {(z, e) in EXISTING_PLANTS} =
    finance_rate[tech_ccgt] * (1 + 1/(1+finance_rate[tech_ccgt])^ep_max_age_years[z, e]-1) * ep_overnight_cost[z, e];

# discount capital costs to a lump-sum value at the start of the study.
# Reported costs are in $/kW, but we need $/MW, so we multiply by 1000.
param ep_capital_cost {(z, e) in EXISTING_PLANTS} =
    ep_capital_cost_annual_payment[z, e] * 1000
    * (1-(1/(1+discount_rate)^(ep_end_year[z, e]-start_year)))/discount_rate
    * discount_factor[start_year];

# cost per MW to operate a plant in any future period, discounted to start of study
param ep_fixed_cost {(z, e) in EXISTING_PLANTS, p in PERIODS} =
    ep_fixed_o_m[z, e] * 1000 * (1-(1/(1+discount_rate)^(years_per_period))/discount_rate
    * discount_factor[p];

# all variable costs ($/MWh) for generating a MWh of electricity in some
# future hour, from each existing project, discounted to the reference year
# note: we divide heat_rate by 1000 to go from Btu/kWh to MBtu/MWh
param ep_variable_cost {(z, e) in EXISTING_PLANTS, h in HOURS} =
    hours_in_sample[h] * (
        ep_variable_o_m[z, e]
        + ep_heat_rate[z, e]/1000 * fuel_cost_hourly[ep_fuel[z, e], h]
    ) * discount_factor[period[h]];
# cost per MW for transmission lines
# TODO: use a transmission_annual_cost_change factor to make this vary between vintages
param transmission_annual_payment {(z1, z2) in TRANS_LINES, v in VINTAGE_YEARS} =
    transmission_finance_rate * (1 + 1/((1+transmission_finance_rate)^transmission_max_age_years-1))
    * transmission_cost_per_mw_km * transmission_length_km[z1, z2];

# date when a when a transmission line built of each vintage will stop being included in the simulation
# note: if it would be expected to retire between study periods,
# it is kept running (and annual payments continue to be made).
param transmission_end_year (v in VINTAGE_YEARS) =
    min(end_year, v+ceil(transmission_max_age_years/years_per_period) *years_per_period);

# discounted cost per MW
param transmission_cost_per_mw {(z1, z2) in TRANS_LINES, v in VINTAGE_YEARS} =
    transmission_annual_payment[z1, z2, v]
    * (1-(1/(1+discount_rate)^(transmission_end_year[v] - v)))/discount_rate
    * discount_factor[v];

# date when a when local T&D infrastructure of each vintage will stop being included in the simulation
# note: if it would be expected to retire between study periods,
# it is kept running (and annual payments continue to be made).
param local_td_end_year (v in VINTAGE_YEARS) =
    min(end_year, v+ceil(local_td_max_age_years/years_per_period) *years_per_period);

# discounted cost per MW for local T&D
# note: instead of bringing in an annual payment directly (above), we could calculate it as
# = local_td_finance_rate * (1 + 1/((1+local_td_finance_rate)^local_td_max_age_years-1))
# * local_td_real_cost_per_mw;
param local_td_cost_per_mw (v in VINTAGE_YEARS) =
    local_td_annual_payment_per_mw
    * (1-(1/(1+discount_rate)^(local_td_end_year[v] - v)))/discount_rate
    * discount_factor[v];

#######
# total cost of existing hydro plants (including capital and O&M)
# note: it would be better to handle these costs more endogenously.
# for now, we assume the nameplate capacity of each plant is equal to its peak allowed output.

# the total cost per MW for existing hydro plants
# (the discounted stream of annual payments over the whole study)
param hydro_cost_per_mw =
    hydro_annual_payment_per_mw
    * (1-(1/(1+discount_rate)^(end_year-start_year)))/discount_rate
    * discount_factor[start_year];
# make a guess at the nameplate capacity of all existing hydro
param hydro_total_capacity =
    sum {(z, s) in PROJ_HYDRO} (max {(z, s, d) in PROJ_HYDRODATES} max_hydro_flow[z, s, d]);

#####
# Supply curve for interruptible load (in discounted-cost terms)

# This stairstepped curve is specified by a list of marginal costs
# corresponding to various levels of usage of interruptible load
# (the marginal cost rises as we use more of it)
# Each pair of marginal cost and usage level is known as a “breakpoint”
# indexing list of the segments of the interruptible load cost curve
# this includes one element for the right edge of each segment of the cost curve
set INTERRUPTIBLE_LOAD_BREAKPOINTS ordered = 1 .. interruptible_load_cost_segment_count;

# list of the percentages of peak load for each cost curve breakpoint
# (e.g., interruptible load equal to 0.01, 0.02, ... * peak load for the zone)
param interruptible_load_breakpoint_share {bp in INTERRUPTIBLE_LOAD_BREAKPOINTS}
  = bp * interruptible_load_max_share/interruptible_load_cost_segment_count;

# corresponding amounts of interruptible load (in MW) in each load zone
param interruptible_load_breakpoint_mw {z in LOAD_ZONES, p in PERIODS, bp in
INTERRUPTIBLE_LOAD_BREAKPOINTS}
  = interruptible_load_breakpoint_share[bp] * max {h in HOURS: period[h]=p} system_load_fixed[z, h];

# calculate the marginal cost per MW of interruptible load between each breakpoint.
# (costs are for additional capacity up to and including that breakpoint)
# For now, we assume the marginal cost increases linearly as the percentage of interruptible load increases.
# (In future, it would be possible to create different stairstepped supply curves.)
# note: this creates a stairstep supply curve whose right edge matches
# with a straightline supply curve with the same average slope. That way, the model will never
# use more interruptible load than is available at each cost point. But this does tend to
# overstate the total costs, compared to a centered stairstep supply curve, at least for a
# pay-as-bid type auction or social welfare calculation where producer surplus is counted as a benefit.
# (On the other hand, if the breakpoints are close together, this error will be small, and
# in fact the cost of interruptible load will be much higher in a uniform-price auction.)
param interruptible_load_cost_slope {z in LOAD_ZONES, p in PERIODS, bp in INTERRUPTIBLE_LOAD_BREAKPOINTS} =
  interruptible_load_cost_per_kw_year_per_percent_peak_load * 1000
  * interruptible_load_breakpoint_share[bp] * 100
  * annual_cost_weight[p];

# Total cost of developing various amounts of interruptible load.
# This is useful for the linear constraint that keeps total costs at or above the appropriate level.
param interruptible_load_total_cost {z in LOAD_ZONES, p in PERIODS, bp in INTERRUPTIBLE_LOAD_BREAKPOINTS} =
  sum {bp2 in INTERRUPTIBLE_LOAD_BREAKPOINTS: bp2 <= bp}
  interruptible_load_cost_slope[z, p, bp2] *
  (interruptible_load_breakpoint_mw[z, p, bp2] - if ord(bp2)=1 then 0 else interruptible_load_breakpoint_mw[z, p, prev(bp2)]);

#######
# Demand curve for electricity on an annual basis,
# in MWh and dollar terms, specific to each load zone and period, with discounting.
# The demand curve for each load zone needs to show marginal benefits in dollars for each extra
# unit of electricity delivered. The electricity could be expressed in % of base (which is how
# the overall demand curve is expressed), or in terms of peak MW served or total MWh delivered.
# It would be mathematically simpler to use the % of base, but then the marginal prices are only
# "true" for a particular base level of demand. If the prices are expressed per MWh delivered,
# then they will be more robust if we change the base quantity of electricity demanded, and they
# will be easier to interpret (e.g., "the marginal value of delivering 1 MWh spread through the year
# with the normal load pattern for Fresno is $89" instead of "if we raise the year-round supply of
# power in Fresno by 1% it will yield $92012312 worth of benefits").
# So I express the amount of power demanded in MWh, and calculate the cost of delivering various
# numbers of MWh in each load zone.
# (this requires multiplying and dividing by annual_demand_quantity_base_mwh[z,p] in various places)

# calculate the base-case power demand per year in each zone, in MWh
param annual_demand_quantity_base_mwh {z in LOAD_ZONES, p in PERIODS} =
    sum {h in HOURS: period[h] = p} system_load_fixed[z, h] * hours_in_sample[h] / years_per_period;

# find the MWh levels corresponding to breakpoints on the demand curve
param annual_demand_quantity_mwh {z in LOAD_ZONES, p in PERIODS, bp in ANNUAL_DEMAND_BREAKPOINTS} =
    annual_demand_quantity_vs_base[bp] * annual_demand_quantity_base_mwh[z, p];

# calculate the marginal benefit (dollars per MWh, in present-value terms) of
# delivering power when the total annual system load is at various levels.
# (benefits are for additional power production when the total demand is at or beyond each breakpoint)
param annual_demand_benefit_slope {z in LOAD_ZONES, p in PERIODS, bp in ANNUAL_DEMAND_BREAKPOINTS} =
    annual_demand_price_vs_base[bp] * annual_demand_price_base[z] * annual_cost_weight[p];

# Total benefit (in dollars) of delivering various amounts of annual power (in MWh)
# This is the integral of the price vs power supply curve up to each breakpoint.
# It is useful for the linear constraint that keeps total costs at or above the appropriate level.
# note: we don't know the total value of supplying power up to the first breakpoint, so we just assume zero.
# The marginal values between breakpoints are what actually matter, but this means the objective function
# cannot be interpreted as reporting the "true" net benefit of generating power.
param annual_demand_benefit_total {z in LOAD_ZONES, p in PERIODS, bp in ANNUAL_DEMAND_BREAKPOINTS} =
    if ord(bp) = 1 then 0 else
    annual_demand_benefit_total[z, p, prev(bp)] +
    annual_demand_benefit_slope[z, p, prev(bp)] * (annual_demand_quantity_mwh[z, p, bp] - annual_demand_quantity_mwh[z, p, prev(bp)]);

# "discounted" system load, for use in calculating levelized cost of power.
param system_load_discounted =
    sum {z in LOAD_ZONES, d in DATES, h in HOURS: date[h] = d} (hours_in_sample[h] * (system_load_fixed[z, h] + system_load_moveable[z, d])
    * discount_factor[period[h]]);

# specific sets that are used often
# some of these are also important to the logic of the model,
# i.e., we don't consider using projects during periods that are beyond their retirement year
# (those post-retirement years are simply excluded from the indexing set)
# project-vintage combinations that can be installed
set PROJECT_VINTAGES = setof {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS: v >= min_vintage_year[t]} {z, t, s, o, v};

# technology-site-vintage-hour combinations for dispatchable projects
# (i.e., all the project-vintage combinations that are still active in a given hour of the study)
set PROJ_DISPATCH_VINTAGE_HOURS :=
  { (z, t, s, o) in PROJ_DISPATCH, v in VINTAGE_YEARS, h in HOURS: v >= min_vintage_year[t] and v <= period[h] < project_end_year[t, v]};

# technology-site-vintage-hour combinations for intermittent (non-dispatchable) projects
set PROJ_INTERMITTENT_VINTAGE_HOURS :=
  { (z, t, s, o) in PROJ_INTERMITTENT, v in VINTAGE_YEARS, h in HOURS: v >= min_vintage_year[t] and v <= period[h] < project_end_year[t, v]};

# plant-period combinations when existing plants can run
# these are the times when a decision must be made about whether a plant will be kept available for the year
# or mothballed to save on fixed O&M (or fuel, for baseload plants)
# note: something like this could be added later for early retirement of new plants too
set EP_PERIODS :=
  { (z, e) in EXISTING_PLANTS, p in PERIODS: ep_vintage[z, e] <= p < ep_end_year[z, e]};

# plant-hour combinations when existing non-baseload plants can be dispatched
set EP_DISPATCH_HOURS :=
  { (z, e) in EXISTING_PLANTS, h in HOURS: not ep_baseload[z, e] and ep_vintage[z, e] <= period[h] < ep_end_year[z, e]};

# plant-period combinations when existing baseload plants can run
set EP_BASELOAD_PERIODS :=
  { (z, e, p) in EP_PERIODS: ep_baseload[z, e]};

# trans_line-vintage-hour combinations for which dispatch decisions must be made
set TRANS_VINTAGE_HOURS :=
  { (z1, z2) in TRANS_LINES, v in VINTAGE_YEARS, h in HOURS: v <= period[h] < transmission_end_year[v]};

# local_td-vintage-hour combinations which must be reconciled
set LOCAL_TD_HOURS :=
  { z in LOAD_ZONES, v in VINTAGE_YEARS, h in HOURS: v <= period[h] < local_td_end_year[v]};

#### VARIABLES ####

# number of MW to install in each project at each date (vintage)
var InstallGen {PROJECT_VINTAGES} >= 0;

# number of MW to generate from each project, in each hour
var DispatchGen {PROJ_DISPATCH, HOURS} >= 0;

# number of MW of moveable load to serve in each hour
var DispatchSystemLoad {LOAD_ZONES, HOURS} >= 0;
# number of MW generated by intermittent renewables
# this is not a decision variable, but is useful for reporting
# (well, it would be useful for reporting, but it takes 63 MB of ram for
# 240 hours x 2 vintages and grows proportionally to that product)
#var IntermittentOutput (z, t, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS
# = (1-forced_outage_rate[t]) * cap_factor[z, t, o, h] * InstallGen[z, t, o, v];

# share of existing plants to operate during each study period.
# this should be a binary variable, but it's interesting to see
# how the continuous form works out
var OperateEPDuringYear (EP_PERIODS) >= 0, <= 1;

# number of MW to generate from each existing dispatchable plant, in each hour
var DispatchEP (EP_DISPATCH_HOURS) >= 0;

# number of MW to install in each transmission corridor at each vintage
var InstallTrans (TRANS_LINES, VINTAGE_YEARS) >= 0;

# number of MW to transmit through each transmission corridor in each hour
var DispatchTransTo (TRANS_LINES, HOURS) >= 0;
var DispatchTransFrom (TRANS_LINES, HOURS) >= 0;
var DispatchTransTo_Reserved (TRANS_LINES, HOURS) >= 0;
var DispatchTransFrom_Reserved (TRANS_LINES, HOURS) >= 0;

# amount of local transmission and distribution capacity
# (to carry peak power from transmission network to distributed loads)
var InstallLocalTD (LOAD_ZONES, VINTAGE_YEARS) >= 0;

# amount of pumped hydro to store and dispatch during each hour
# note: the amount "stored" is the number of MW that can be generated using
# the water that is stored,
# so it takes 1/pumped_hydro_efficiency MWh to store 1 MWh
var StorePumpedHydro (PROJ_PUMPED_HYDRO, HOURS) >= 0;
var DispatchPumpedHydro (PROJ_PUMPED_HYDRO, HOURS) >= 0;
var StorePumpedHydro_Reserve (PROJ_PUMPED_HYDRO, HOURS) >= 0;
var DispatchPumpedHydro_Reserve (PROJ_PUMPED_HYDRO, HOURS) >= 0;

# simple hydro is dispatched on an aggregated basis, using a schedule that shows the
# amount of discretionary hydro to dispatch during each study period, in each zone,
# season (Jan-Mar, Apr-Jun, etc.) and hour
var HydroDispatchShare (PERIODS, LOAD_ZONES, SEASONS_OF_YEAR, HOURS_OF_DAY) >= 0;
var HydroDispatchShare_Reserve (PERIODS, LOAD_ZONES, SEASONS_OF_YEAR, HOURS_OF_DAY) >= 0;

# the total amount of generic demand response that will be developed
#var AcceptDemandResponseMW >= 0;

# amount of interruptible load used in each load zone during each period (in MW)
var AcceptInterruptibleLoad (z in LOAD_ZONES, p in PERIODS) >= 0;
var InterruptibleLoadCost (z in LOAD_ZONES, p in PERIODS) >= 0;

# amount of annual demand satisfied in each load zone during each period (in MW)
var ClearAnnualDemand (z in LOAD_ZONES, p in PERIODS) >= 0 default annual_demand_quantity_base_mwh[z, p];
var AnnualDemandBenefit (z in LOAD_ZONES, p in PERIODS) >= 0;

#### OBJECTIVES ####
# total cost of power, including carbon tax
# TODO: it would be easier to reuse parts of this for other things if
# it broke down costs by study period, and separated carbon emissions from other costs,
# and did the discounting here directly, rather than using pre-discounted cost terms.

minimize Power_Cost:
    sum {(z, t, s, o, v) in PROJECT_VINTAGES} 
    InstallGen[z, t, s, o, v] * fixed_cost[z, t, s, o, v] 
    + sum {(z, t, s, o) in PROJ_DISPATCH, h in HOURS} 
    DispatchGen[z, t, s, o, h] * (variable_cost[t, h] + carbon_cost_per_mwh[t, h]) 
    + sum {(z, e) in EXISTING_PLANTS} ep_size_mw[z, e] * ep_capital_cost[z, e] 
    + sum {(z, e, p) in EP_PERIODS} 
    OperateEPDuringYear[z, e, p] * ep_size_mw[z, e] * ep_fixed_cost[z, e, p] 
    + sum {(z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p} 
    OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * 
    ep_size_mw[z, e] * ep_variable_cost[z, e, h] + ep_carbon_cost_per_mwh[z, e, h]) 
    + sum {(z, e, h) in EP_DISPATCH_HOURS} 
    DispatchEP[z, e, h] * ep_variable_cost[z, e, h] + ep_carbon_cost_per_mwh[z, e, h]) 
    + hydro_cost_per_mw * hydro_total_capacity 
    + sum {(z1, z2) in TRANS_LINES, v in VINTAGE_YEARS} 
    InstallTrans[z1, z2, v] * transmission_cost_per_mw[z1, z2, v] 
    + sum {(z1, z2) in TRANS_LINES} 
    transmission_cost_per_mw[z1, z2, first(PERIODS)] * (existing_transmission_from[z1, z2] + 
    existing_transmission_to[z1, z2])/2 
    + sum {z in LOAD_ZONES, v in VINTAGE_YEARS} 
    InstallLocalTD[z, v] * local_td_cost_per_mw[v] 
    + sum {z in LOAD_ZONES, p in PERIODS} InterruptibleLoadCost[z, p] 
    - sum {z in LOAD_ZONES, p in PERIODS} AnnualDemandBenefit[z, p] 

# this alternative objective is used to reduce transmission flows to 
# zero in one direction of each pair, and to minimize needless flows 
# around loops, or shipping of unneeded power to neighboring zones,
# so it is more clear how much surplus power is being generated and where 
minimize Transmission_Usage:
    sum {(z1, z2) in TRANS_LINES, h in HOURS} 
    (DispatchTransTo[z1, z2, h] + DispatchTransFrom[z1, z2, h]);

##### CONSTRAINTS #####

# system needs to meet the load in each load zone in each hour 
# note: power is deemed to flow from z1 to z2 if positive, reverse if negative 
subject to Satisfy_Load {z in LOAD_ZONES, h in HOURS}:
    sum {(z, t, s, o) in PROJ_DISPATCH} DispatchGen[z, t, s, o, h] 
    + sum {(z, t, s, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS} 
    (1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v] 

# new dispatchable projects 
(sum {(z, t, s, o) in PROJ_DISPATCH} DispatchGen[z, t, s, o, h]) 

# output from new intermittent projects 
+ (sum {(z, t, s, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS} 
(1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v]) 

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# existing baseload plants
+ sum {{z, e, p} in EP_BASELOAD_PERIODS: p=period[h]} (OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e])

# existing dispatchable plants
+ sum {{z, e, h} in EP_DISPATCH_HOURS} OperateEPDuringYear[z, e, period[h]] * ep_size_mw[z, e]

# pumped hydro, de-rated to reflect occasional unavailability of the hydro plants
+ (1 - forced_outage_rate_hydro) * (sum {{z, s} in PROJ_PUMPED_HYDRO} DispatchPumpedHydro[z, s, h])
- (1 - forced_outage_rate_hydro) * (1/pumped_hydro_efficiency) *
  (sum {{z, s} in PROJ_PUMPED_HYDRO} StorePumpedHydro[z, s, h])

# simple hydro, dispatched using the season-hour schedules chosen above
# also de-rated to reflect occasional unavailability
+ (1 - forced_outage_rate_hydro) *
  (min_hydro_dispatch_all_sites[z, date[h]])
  + HydroDispatchShare[period[h], z, season_of_year[h], hour_of_day[h]]
  * (avg_hydro_dispatch_all_sites[z, date[h]] - min_hydro_dispatch_all_sites[z, date[h]]) * 24

# transmission into and out of the zone
+ (sum {{z, z2} in TRANS_LINES} transmission_efficiency[z, z2] * DispatchTransTo[z, z2, h] - DispatchTransFrom[z, z2, h])
- (sum {{z1, z} in TRANS_LINES} DispatchTransTo[z1, z, h] - transmission_efficiency[z1, z] * DispatchTransFrom[z1, z, h])

>= system_load_fixed[z, h] * ClearAnnualDemand[z, period[h]]
  / max(annual_demand_quantity_base_mwh[z, period[h]], 1e-6)
+ DispatchSystemLoad[z, h];

# same on a reserve basis
# note: these are not prorated by forced outage rate, because that is incorporated in the reserve margin
# It is also assumed that moveable load can be shed as needed, so it is not counted here either.
# Interruptible loads are assumed to reduce the load requirements for reserve margin also.
subject to Satisfy_Load_Reserve {z in LOAD_ZONES, h in HOURS}:

# new dispatchable capacity
(sum {{z, t, s, o, v} in PROJ_DISPATCH_VINTAGE_HOURS} InstallGen[z, t, s, o, v])

# output from new intermittent projects
+ (sum {{z, t, s, o, v} in PROJ_INTERMITTENT_VINTAGE_HOURS} cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v])

# existing baseload plants
+ sum {{z, e, p} in EP_BASELOAD_PERIODS: p=period[h]} (OperateEPDuringYear[z, e, p] * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e])

# existing dispatchable capacity
+ sum {{z, e, h} in EP_DISPATCH_HOURS} OperateEPDuringYear[z, e, period[h]] * ep_size_mw[z, e]
pumped hydro
+ \sum_{(z, s) \in \text{PROJ\_PUMPED\_HYDRO}} \text{DispatchPumpedHydro\_Reserve}[z, s, h] \\
- \frac{1}{\text{pumped\_hydro\_efficiency}} \times \\
\sum_{(z, s) \in \text{PROJ\_PUMPED\_HYDRO}} \text{StorePumpedHydro\_Reserve}[z, s, h]

simple hydro, dispatched using the season-hour schedules chosen above
+ \text{min\_hydro\_dispatch\_all\_sites}[z, \text{date}[h]] \\
+ \text{HydroDispatchShare\_Reserve}[\text{period}[h], z, \text{season\_of\_year}[h], \text{hour\_of\_day}[h]] \\
\times (\text{avg\_hydro\_dispatch\_all\_sites}[z, \text{date}[h]] - \text{min\_hydro\_dispatch\_all\_sites}[z, \text{date}[h]]) \times 24

transmission into and out of the zone
+ \sum_{(z, z2) \in \text{TRANS\_LINES}} \left(\text{transmission\_efficiency}[z, z2] \times \text{DispatchTransTo\_Reserve}[z, z2, h] - \text{DispatchTransFrom\_Reserve}[z, z2, h]\right) \\
- \sum_{(z1, z) \in \text{TRANS\_LINES}} \left(\text{DispatchTransTo\_Reserve}[z1, z, h] - \text{transmission\_efficiency}[z1, z] \times \text{DispatchTransFrom\_Reserve}[z1, z, h]\right)

interruptible load contributes to reserve margin, even though it doesn't save energy
it also gets extra credit because it doesn't need to be backed up with a reserve margin
(i.e., it reduces load in the reserve margin calculation)
+ \text{AcceptInterruptibleLoad}[z, \text{period}[h]] \times (1 + \text{planning\_reserve\_margin})

\geq \text{system\_load\_fixed}[z, h] \times (1 + \text{planning\_reserve\_margin}) \\
\times \text{ClearAnnualDemand}[z, \text{period}[h]] / \text{max(annual\_demand\_quantity\_base\_mwh}[z, \text{period}[h]], 1e-6)

total dispatch of moveable load on each day must sum to the pre-specified average value
(this could be a \geq constraint, but that would make spilling of renewable power harder to spot)
subject to \text{Dispatch\_MoveableLoad} (z in \text{LOAD\_ZONES}, d in \text{DATES}): \\
\sum_{h \in \text{HOURS}: \text{date}[h]=d} \text{DispatchSystemLoad}[z, h] = \\
\sum_{h \in \text{HOURS}: \text{date}[h]=d} \text{system\_load\_moveable}[z, d]

pumped hydro dispatch for all hours of the day must be within the limits of the plant
net flow of power (i.e., water) must also match the historical average
// TODO: find better historical averages that reflect net balance of generated and stored power,
// because the values currently used are equal to sum(Dispatch - 1/efficiency * Storage)
subject to \text{Maximum\_DispatchPumpedHydro} (z, s) in \text{PROJ\_PUMPED\_HYDRO}, h in \text{HOURS}:
\text{DispatchPumpedHydro}[z, s, h] \leq \text{max\_hydro\_flow}[z, s, h]
subject to \text{Maximum\_StorePumpedHydro}
\\{(z, s) \in \text{PROJ\_PUMPED\_HYDRO}, h \in \text{HOURS}: \text{min\_hydro\_flow}[z, s, h] < 0\}:
\text{StorePumpedHydro}[z, s, h] \leq -\text{min\_hydro\_flow}[z, s, h]

subject to \text{Average\_PumpedHydroFlow} (z, s) in \text{PROJ\_PUMPED\_HYDRO}, d in \text{DATES}:
\sum_{h \in \text{HOURS}: \text{date}[h]=d} (\text{DispatchPumpedHydro}[z, s, h] - \text{StorePumpedHydro}[z, s, h]) \times \text{hours\_in\_sample}[h]
\leq \sum_{h \in \text{HOURS}: \text{date}[h]=d} \text{avg\_hydro\_flow}[z, s, d] \times \text{hours\_in\_sample}[h]

extra rules to apply when non-pumped sites are also dispatched hourly
subject to \text{Minimum\_DispatchNonPumpedHydro}
\\{(z, s) \in \text{PROJ\_PUMPED\_HYDRO}, h \in \text{HOURS}: \text{min\_hydro\_flow}[z, s, date[h]] \geq 0\}:
\text{DispatchPumpedHydro}[z, s, h] \geq \text{min\_hydro\_flow}[z, s, date[h]]

subject to \text{Maximum\_StoreNonPumpedHydro}
\\{(z, s) \in \text{PROJ\_PUMPED\_HYDRO}, h \in \text{HOURS}: \text{min\_hydro\_flow}[z, s, date[h]] \geq 0\}:
\text{StorePumpedHydro}[z, s, h] = 0
# discretionary hydro dispatch for all hours of the day must sum to 1
# note: dispatch is deemed to happen no matter what (to respect flow constraints),
# but energy supply is later de-rated by hydro forced outage rate
# note: if not all the hours of the day are modeled, then the ones that
# are modeled actually stand in for other ones as well (e.g., if we only
# model 8 hours in the day, then each of those represents 3 hours of
# hydro dispatch). It would be better to replace max_hydro_dispatch_per_hour with
# a new parameter, max_hydro_dispatch_multiple (=24 * max_hydro_dispatch_per_hour),
# then we would require simply that the average hydro dispatch come out to 1,
# instead of the weighted sum.
subject to Maximum_DispatchHydroShare
  \{p in PERIODS, z in LOAD_ZONES, s in SEASONS_OF_YEAR\}:
  \sum \{h in HOURS_OF_DAY\} HydroDispatchShare[p, z, s, h] * (24 / card(HOURS_OF_DAY)) <= 1;

# only part of the discretionary hydro can be dispatched in each hour of the day
subject to MaximumHourly_DispatchHydroShare
  \{p in PERIODS, z in LOAD_ZONES, s in SEASONS_OF_YEAR, h in HOURS_OF_DAY\}:
  0 <= HydroDispatchShare[p, z, s, h] <= max_hydro_dispatch_per_hour;

# same for reserve margin operation
subject to Maximum_DispatchPumpedHydro_Reserve \{(z, s) in PROJ_PUMPED_HYDRO, h in HOURS\}:
  DispatchPumpedHydro_Reserve[z, s, h] <= max_hydro_flow[z, s, date[h]];
subject to Maximum_StorePumpedHydro_Reserve \{(z, s) in PROJ_PUMPED_HYDRO, h in HOURS\}:
  min_hydro_flow[z, s, date[h]] <= StorePumpedHydro_Reserve[z, s, h];
subject to Average_PumpedHydroFlow_Reserve \{(z, s) in PROJ_PUMPED_HYDRO, d in DATES\}:
  \sum \{h in HOURS: date[h]=d\} (DispatchPumpedHydro_Reserve[z, s, h] - StorePumpedHydro_Reserve[z, s, h]) <= \sum \{h in HOURS: date[h]=d\} avg_hydro_flow[z, s, d];
subject to Minimum_DispatchNonPumpedHydro_Reserve \{(z, s) in PROJ_PUMPED_HYDRO, h in HOURS\}:
  DispatchPumpedHydro_Reserve[z, s, h] >= min_hydro_flow[z, s, date[h]];
subject to Maximum_StoreNonPumpedHydro_Reserve \{(z, s) in PROJ_PUMPED_HYDRO, h in HOURS\}:
  StorePumpedHydro_Reserve[z, s, h] = 0;
subject to Maximum_DispatchHydroShare_Reserve
  \{p in PERIODS, z in LOAD_ZONES, s in SEASONS_OF_YEAR\}:
  \sum \{h in HOURS_OF_DAY\} HydroDispatchShare_Reserve[p, z, s, h] <= 1;
subject to MaximumHourly_DispatchHydroShare_Reserve
  \{p in PERIODS, z in LOAD_ZONES, s in SEASONS_OF_YEAR, h in HOURS_OF_DAY\}:
  0 <= HydroDispatchShare_Reserve[p, z, s, h] <= max_hydro_dispatch_per_hour;

# system can only dispatch as much of each project as is EXPECTED to be available
# i.e., we only dispatch up to 1-forced_outage_rate, so the system will work on an expected-value basis
# (this is the base portfolio, more backup generators will be added later to get a lower year-round risk level)
subject to Maximum_DispatchGen
  \{(z, t, s, o) in PROJ_DISPATCH, h in HOURS\}:
  DispatchGen[z, t, s, o, h] <= (1-forced_outage_rate[t]) * \sum \{(z, t, s, o, v, h) in PROJ_DISPATCH_VINTAGE_HOURS\} InstallGen[z, t, s, o, v];
# there are limits on total installations in certain projects
# TODO: adjust this to allow re-installing at the same site after retiring an earlier plant
# (not an issue if the simulation is too short to retire plants)
# or even allow forced retiring of earlier plants if new technologies are better
subject to Maximum_Resource \{ (z, t, s, o) in PROJ_RESOURCE_LIMITED \}:
    \sum \{ (z, t, s, o, v) in PROJECT_VINTAGES \} InstallGen[z, t, s, o, v] <= max_capacity[z, t, s, o];

# existing dispatchable plants can only be used if they are operational this year
subject to EP_Operational
    \{ (z, e, h) in EP_DISPATCH_HOURS \}: DispatchEP[z, e, h] <= 
        OperateEPDuringYear[z, e, period[h]] * (1-ep_forced_outage_rate[z, e]) * ep_size_mw[z, e];

# system can only use as much transmission as is expected to be available
# note: transmission up and down the line both enter positively,
# but the form of the model allows them to both be reduced or increased by a constant,
# so they will both be held low enough to stay within the installed capacity
# (if there were a variable cost of operating, one of them would always go to zero)
# a quick follow-up model run minimizing transmission usage will push one of these to zero.
# TODO: retire pre-existing transmission lines after transmission_max_age_years
#   (this requires figuring out when they were first built!)
subject to Maximum_DispatchTransTo
    \{ (z1, z2) in TRANS_LINES, h in HOURS \}:
        DispatchTransTo[z1, z2, h] <= (1-transmission_forced_outage_rate) * 
            (existing_transmission_to[z1, z2] + \sum \{ (z1, z2, v, h) in TRANS_VINTAGE_HOURS \} InstallTrans[z1, z2, v]);
subject to Maximum_DispatchTransFrom
    \{ (z1, z2) in TRANS_LINES, h in HOURS \}:
        DispatchTransFrom[z1, z2, h] <= (1-transmission_forced_outage_rate) * 
            (existing_transmission_from[z1, z2] + \sum \{ (z1, z2, v, h) in TRANS_VINTAGE_HOURS \} InstallTrans[z1, z2, v]);
subject to Maximum_DispatchTrans_ReserveTo
    \{ (z1, z2) in TRANS_LINES, h in HOURS \}:
        DispatchTransTo_Reserve[z1, z2, h] <= (existing_transmission_to[z1, z2] + \sum \{ (z1, z2, v, h) in TRANS_VINTAGE_HOURS \} InstallTrans[z1, z2, v]);
subject to Maximum_DispatchTrans_ReserveFrom
    \{ (z1, z2) in TRANS_LINES, h in HOURS \}:
        DispatchTransFrom_Reserve[z1, z2, h] <= (existing_transmission_from[z1, z2] + \sum \{ (z1, z2, v, h) in TRANS_VINTAGE_HOURS \} InstallTrans[z1, z2, v]);

# make sure there's enough intra-zone transmission and distribution capacity
# to handle the net distributed loads
# because it is not likely to be called upon just to relieve local T&D congestion.
subject to Maximum_LocalTD
    \{ z in LOAD_ZONES, h in HOURS \}:
        system_load_fixed[z, h] * ClearAnnualDemand[z, period[h]]/max(annual_demand_quantity_base_mwh[z, period[h]], 1e-6) + DispatchSystemLoad[z, h] - \sum \{ (z, t, s, o, h) in PROJ_INTERMITTENT_VINTAGE_HOURS: t=tech_pv \}
            (1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v]) <= \sum \{ (z, v, h) in LOCAL_TD_HOURS \} InstallLocalTD[z, v];
windsun.mod

# interruptible load cannot exceed the target percentage
# (this is conveniently stored in MW terms at the end of the list of cost curve breakpoints)
subject to MaximumInterruptibleLoad {z in LOAD_ZONES, p in PERIODS}:
    AcceptInterruptibleLoad[z, p] <= interruptible_load_breakpoint_mw[z, p, last(INTERRUPTIBLE_LOAD_BREAKPOINTS)];

# the expenditure on interruptible load must exceed all the linear segments of the supply curve
# (it would be better to use a direct piecewise linear formulation, but that seems to be broken in ampl v. 20070903)
subject to PiecewiseInterruptibleLoadCost {z in LOAD_ZONES, p in PERIODS, bp in INTERRUPTIBLE_LOAD_BREAKPOINTS}:
    InterruptibleLoadCost[z, p] >=
        if ord(bp)=1 then
            AcceptInterruptibleLoad[z, p] * interruptible_load_cost_slope[z, p, bp]
        else
            interruptible_load_total_cost[z, p, prev(bp)] + (AcceptInterruptibleLoad[z, p] - interruptible_load_breakpoint_mw[z, p, prev(bp)]) * interruptible_load_cost_slope[z, p, bp]
        ;

# system load must fall within the allowed range of the base-case load
# (upper and lower limits correspond to the first and last breakpoints of the demand curve)
subject to MinimumMaximumAnnualDemand {z in LOAD_ZONES, p in PERIODS}:
    annual_demand_quantity_mwh[z, p, first(ANNUAL_DEMAND_BREAKPOINTS)] <= ClearAnnualDemand[z, p] <= annual_demand_quantity_mwh[z, p, last(ANNUAL_DEMAND_BREAKPOINTS)];

# the benefit of satisfying demand must be below all the linear segments of the supply curve
# (it would be better to use a direct piecewise linear formulation, but that is broken in ampl v. 20070903)
# we could ignore the last segment, because the load can never exceed the last breakpoint,
# but that would make AnnualDemandBenefit unbounded when there is only one breakpoint in the demand curve
subject to PiecewiseAnnualDemandBenefit {z in LOAD_ZONES, p in PERIODS, bp in ANNUAL_DEMAND_BREAKPOINTS}:
    AnnualDemandBenefit[z, p] <=
        annual_demand_benefit_total[z, p, bp]
        + (ClearAnnualDemand[z, p] - annual_demand_quantity_mwh[z, p, bp]) * annual_demand_benefit_slope[z, p, bp];
This script loads the model (windsun.mod) into memory and initializes it with suitable data. Generally, the Switch model is run by executing the following commands in ampl:

```plaintext
cd <data file directory>;
include ../windsun.run;
solve;
```

```plaintext
# note: this script should be called from a subdirectory
# holding all the tab files.
# it assumes that the model itself is at the next higher directory level
reset;
if match($version, 'Darwin') > 0 then {
    #option solver cbc;
    option solver cplex_auto;
    option cplex_options 'primalopt lpdisplay=1';
} else {
    option solver cplexamp;
    option cplex_options 'primalopt lpdisplay=1';
}
option presolve 0;
model ../windsun.mod;
data ../windsun.dat;
data ../generator_costs.dat;
```

```plaintext
table study_hours IN: HOURS <- [hour], period, date, hours_in_sample, month_of_year, hour_of_day;
read table study_hours;
```

```plaintext
table load_zones IN: LOAD_ZONES <- [load_zone], load_zone_x, load_zone_y;
read table load_zones;
```

```plaintext
table existing_plants IN:
    EXISTING_PLANTS <- [load_zone, plant_code],
    ep_size_mw ~ size_mw, ep_fuel ~ fuel, ep_heat_rate ~ heat_rate,
    ep_vintage ~ start_year, ep_max_age_years ~ max_age,
    ep_overnight_cost ~ overnight_cost, ep_fixed_o_m ~ fixed_o_m, ep_variable_o_m ~ variable_o_m,
    ep_forced_outage_rate ~ forced_outage_rate, ep_scheduled_outage_rate ~ scheduled_outage_rate,
    ep_baseload ~ baseload, ep_cogen ~ cogen;
read table existing_plants;
```

```plaintext
table trans_lines IN:
    TRANS_LINES <- [load_zone_start, load_zone_end], tid, transmission_length_km,
    transmission_efficiency, existing_transmission_from, existing_transmission_to;
read table trans_lines;
```
table system_load IN: [load_zone, hour], system_load_fixed ~ system_load;
read table system_load;

table max_capacity IN:
   PROJRESOURCELIMITED <- [load_zone, technology, site, orientation], max_capacity;
read table max_capacity;

table connect_cost IN:
   [load_zone, technology, site, orientation], connect_length_km, connect_cost_per_kw;
read table connect_cost;

table cap_factor IN:
   PROJINTERMITTENTHOURS <- [load_zone, technology, site, orientation, hour], cap_factor;
read table cap_factor;

table hydro IN:
   PROJHYDRODATES <- [load_zone, site, date],
   avg_hydro_flow ~ avg_flow, min_hydro_flow ~ min_flow, max_hydro_flow ~ max_flow;
read table hydro;

# set and parameters used to make carbon cost curves
set CARBON_COSTS;

# parameter used to track execution times
param curtime;

# name of the scenario (includes model and scenario name)
param scenario_name symbolic default sub(_cd, "\.^/(\^[^/]+/[^/]+$)\", "1");
#read scenario_name <scenario_name.txt;

# scratch parameter for reading files from disk
# (without something like this, it's impossible to read from disk without creating a new parameter,
# and that can't be done within a loop)
param readfile symbolic;

# NOTE: everything below is a command that can be copied and pasted (without the #) into ampl
# to look at the results

# how much of the elastic demand was satisfied?
# display {z in LOAD_ZONES, p in PERIODS: annual_demand_quantity_base_mwh[z, p] > 0} ClearAnnualDemand[z, p]/annual_demand_quantity_base_mwh[z, p];

# what fraction of the available interruptible load was contracted?
# display {z in LOAD_ZONES, p in PERIODS: interruptible_load_breakpoint_mw[z, p, 1] > 0} AcceptInterruptibleLoad[z, p]*interruptible_load_max_share/interruptible_load_breakpoint_mw[z, p, last(INTERRUPTIBLE_LOAD_BREAKPOINTS)];

# annual installations
#display {v in VINTAGE_YEARS, t in TECHNOLOGIES} sum {(z, t, s, o) in PROJECTS} InstallGen[z, t, s, o, v];
# total installations
#display {t in TECHNOLOGIES} sum {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS} InstallGen[z, t, s, o, v];
# new transmission MW-km
# display sum {v in VINTAGE_YEARS, (z1, z2) in TRANS_LINES} InstallTrans[z1, z2, v] * transmission_length_km[z1, z2];
# display {v in VINTAGE_YEARS} sum {(z1, z2) in TRANS_LINES} InstallTrans[z1, z2, v] * transmission_length_km[z1, z2];
# existing trans MW-km
# display sum {(z1, z2) in TRANS_LINES} max(existing_transmission_to[z1, z2], existing_transmission_from[z1, z2]) * transmission_length_km[z1, z2];

# reset cap_factor to zero for all renewables during the system peak hour (takes at least a few minutes)
# let {p in PERIODS, (z, t, s, o, h) in PROJ_INTERMITTENT_HOURS: period[h]=p and sum {z2 in LOAD_ZONES} system_load[z2,h] = max {h2 in HOURS: period[h2]=p} sum{z2 in LOAD_ZONES} system_load[z2,h2]} cap_factor[z, t, s, o, h] := 0;

# much faster:
# set PEAK_HOURS = setof {p in PERIODS, h in HOURS: period[h]=p and sum {z in LOAD_ZONES} system_load[z,h] = max {h2 in HOURS: period[h2]=p} sum{z in LOAD_ZONES} system_load[z,h2]} (h);
# let {(z, t, s, o, h) in PROJ_INTERMITTENT_HOURS : h in PEAK_HOURS} cap_factor[z, t, s, o, h] := 0;

#display 1 - (sum {(z, t, s, o) in PROJ_DISPATCH, h in HOURS: vintage_period[h]=last(VINTAGES)} DispatchGen[z, t, s, o, h])/(sum {z in LOAD_ZONES, h in HOURS: vintage_period[h]=last(VINTAGES)} system_load[z, h]);

#let {(z, t, s, o, h) in PROJ_HYDRO_HOURS} avg_hydro_flow[z, s, h]=0; let {(z, s, h) in PROJ_HYDRO_HOURS} max_hydro_flow[z, s, h]=0; let {(z, s, h) in PROJ_HYDRO_HOURS} min_hydro_flow[z, s, h]=0;

#display {t in TECHNOLOGIES} sum {(z, t, s, o) in PROJ_DISPATCH, h in HOURS} DispatchGen[z, t, s, o, h];

#display {(t, s) in PROJECTS): sum {v in VINTAGES} Install[t, s, v];

# display {p in PERIODS, z in setof {{z,s} in PROJ_SIMPLE_HYDRO} (z), s in SEASONS_OF_YEAR, h in HOURS_OF_DAY: s=3} floor(10^(40*HydroDispatchShare[p, z, s, h]));

# display {z in LOAD_ZONES, p in PERIODS: interruptible_load_breakpoint_mw[z, p, 1] > 0} AcceptInterruptibleLoad[z, p]*interruptible_load_max_share/interruptible_load_breakpoint_mw[z, p, last(INTERRUPTIBLE_LOAD_BREAKPOINTS)];
A.2 Data Files

The first two files shown here (windsun.dat and generator_costs.dat) provide general descriptions of technologies, fuel costs, etc. These are stored in the top level directory used for the Switch model, along with windsun.mod. They are generally reused for multiple scenarios.

The remaining files describe the loads and resources available for an individual scenario. They are stored in a subdirectory of the main model directory, which I refer to as <data file directory>. This directory can have any name you choose, and there can be more than one <data file directory>, with different names. The model should be invoked from the specific <data file directory> for the scenario that you are interested in (as described in the section on windsun.run). This makes it possible to switch easily among many alternative sets of resource data.

I have included complete copies of windsun.dat and generator_costs.dat, and small examples of the load and resource description files.

A.2.1 windsun.dat

This file gives values for all the parameters of the model that don’t need to be represented in large tables.

windsun.dat

```plaintext
# data file params.dat

# the year to which costs should be discounted
param base_year := 2007;

# annual rate (real) to use to discount future costs to current year
param discount_rate := 0.03;

# required rates of return (real) for generators and transmission lines
param finance_rate default 0.06 := DistPV 0.03;
param transmission_finance_rate := 0.06;

# retirement age for transmission lines
param transmission_max_age_years := 20;

# cost per mw-km for transmission lines
param transmission_cost_per_mw_km := 1000;

# forced outage rate for transmission lines, used for probabilistic dispatch(!)
param transmission_forced_outage_rate := 0.01;
```
# parameters for intra-zone transmission and distribution
# MID has a demand charge of $8.80/kW each month; this works out to $105,600/MW-year
# TODO: find a better source than this (start with E3 2004)
param local_td_annual_payment_per_mw := 100000;
param local_td_max_age_years := 20;

# forced outage rate for hydroelectric dams
# this is used to de-rate the planned power production
# TODO: get a better number for this (0.02 is made up)
param forced_outage_rate_hydro := 0.02;

# round-trip efficiency for storing power via a pumped hydro system
# TODO: find plant-specific numbers for this (0.8 is made up)
param pumped_hydro_efficiency := 0.8;

# maximum share of each day's "discretionary" hydro flow
# (everything between the minimum_hydro_flow and the average_hydro_flow)
# that can be dispatched in a single hour
# Higher values will produce narrower, taller hydro dispatch schedules,
# but also more "baseload" hydro.
param max_hydro_dispatch_per_hour = 0.167;

# "carrying cost" for hydro and pumped hydro facilities ($/MWp/yr)
# this is calculated as
# $1500/kW * 1000 kW/MW * 0.061 (capital recovery factor for a 70-year project at 6% interest)
# + 13/kW * 1000 kW/MW (fixed O&M per MW)
# + 3.3/MWh * 8760 * 0.3 h/y (variable O&M and approx. capacity factor for CA hydro projects [0.26 for all projects,
# 0.35 for simple hydro])
# (this works out to about $43/MWh)
# TODO: calculate hydro costs endogenously
# (that will require some neat way of getting hydro plant and cost data into ampl,
# maybe via existing_plants.tab; that will also require adding a flag to prevent
# the model from trying to dispatch these plants along with the gas and coal ones)
param hydro_annual_payment_per_mw := 113172;

# planning reserve margin - fractional extra load the system must be able to serve
# when there are no forced outages
param planning_reserve_margin = 0.15;

# elasticity of interruptible load
# this is the amount (in dollars per kw-year) by which the cost of
# interruptible load increases for each percent of the system peak load
# that is satisfied with interruptible load
#param interruptible_load_cost_per_kw_year_per_percent_peak_load := 19;

# the maximum amount of interruptible load that can be used in any load zone
# (specified as a fraction of the peak load, e.g., 0.20)
#param interruptible_load_max_share := 0.05;

# the total cost of developing interruptible load is quadratic in the
# amount developed, but we approximate it using a piecewise-linear curve.
# this tells how many segments are in that curve
#param interruptible_load_cost_segment_count := 20;
# list of fuel types
set FUELS := Gas Coal Nuclear Wind Solar Geothermal;

# Names of intermittent and resource-limited technologies.
param tech_ccgt := "CCGT";
param tech_ct := "CT100";
param tech_pv := "DistPV";
param tech_trough := "Trough";
param tech_wind := "Wind";

# default values for projects that don't have sites or orientations
param site_unspecified := "na";
pardon orient_unspecified := "na";

# years that could be studied
# (this must exactly match the years shown in the fuel_cost table)
set YEARS :=
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
2024
2025
2026
2027
2028
2029
2030
2031
2032
2033
2034
2035
2036
2037
2038
2039
2040;
# year by year fuel costs
# from CEC Generator Cost Summary 3.xls (based on CEC Cost of Generation Report)
# NOTE: data series begins in 2006, so I assume fuel costs were the same in 2005
# TODO: find comparable costs for 2005
# TODO: switch from gasified coal to pulverized coal
# TODO: switch to AZ/NV coal and uranium prices, e.g., in
#   Resources.05-020-Appendix%20F.pdf
# TODO: update to use forecasts from 2007 IEPR
#   (see Dissertation References.doc)

param fuel_cost :
    Gas     Nuclear  Coal :=
2005    7.17      0.56    1.60
2006    7.17      0.56    1.60
2007    8.34      0.63    1.47
2008    6.67      0.73    1.64
2009    6.57      0.85    1.63
2010    5.34      0.99    1.61
2011    6.68      1.16    1.57
2012    6.19      1.35    1.65
2013    7.31      1.57    1.68
2014    6.56      1.83    1.71
2015    7.35      2.20    1.74
2016    7.29      2.20    1.77
2017    7.22      2.20    1.80
2018    7.56      2.20    1.83
2019    7.90      2.20    1.86
2020    7.89      2.20    1.89
2021    7.88      2.20    1.92
2022    8.12      2.20    1.94
2023    8.37      2.20    1.98
2024    8.51      2.20    1.97
2025    8.65      2.20    2.00
2026    8.80      2.20    2.04
2027    8.97      2.20    2.06
2028    9.16      2.20    2.09
2029    9.34      2.20    2.12
2030    9.50      2.20    2.15
2031    9.68      2.20    2.18
2032    9.87      2.20    2.21
2033    10.07     2.20    2.24
2034    10.26     2.20    2.26
2035    10.45     2.20    2.29
2036    10.65     2.20    2.29
2037    10.85     2.20    2.29
2038    11.06     2.20    2.29
2039    11.27     2.20    2.29
2040    11.49     2.20    2.29
;

# cost of carbon emissions ($/tonneCO2)
param carbon_cost := 30;
A.2.2 generator_costs.dat

This describes each type of generator that the model is allowed to build in future years.

param: TECHNOLOGIES:

<table>
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<tr>
<th>generator</th>
<th>price_year</th>
<th>min_vintage_year</th>
<th>overnight_cost</th>
<th>connect_cost_per_kw_generic</th>
<th>fixed_o_m</th>
<th>variable_o_m</th>
<th>overnight_cost_change</th>
<th>fixed_o_m_change</th>
<th>variable_o_m_change</th>
<th>fuel</th>
<th>heat_rate</th>
<th>construction_time_years</th>
<th>max_age_years</th>
<th>forced_outage_rate</th>
<th>scheduled_outage_rate</th>
<th>intermittent</th>
<th>resource_limited</th>
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<td>CCGT</td>
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<td>2005</td>
<td>752</td>
<td>2005</td>
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<td>0.3300</td>
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<td>7080</td>
<td>2.000</td>
<td>20</td>
<td>0.046</td>
<td>0.038</td>
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<td>2005</td>
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<td>0.000</td>
<td>0.000</td>
<td>Gas</td>
<td>9266</td>
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<td>0.000</td>
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<td>0.005</td>
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<td>2006</td>
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<td>45</td>
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<td>25</td>
<td>0.010</td>
<td>0.010</td>
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<td>1</td>
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<td>2006</td>
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<td>0.030</td>
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<td>2010</td>
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<td>-0.009</td>
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<td>0.030</td>
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<td>-0.016</td>
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<td># Sterling</td>
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</tbody>
</table>
A.2.3 study_hours.tab

This lists all the investment periods, dates and hours for which the model will be run. Most other data files (e.g., system_load.tab and capacity_factor.tab) must provide data for exactly the same set of hours.

The index numbers for each date and hour can have any value you want, as long as each one is unique. Here I have created date codes by combining the last two digits of the study period, and two digits each indicating the historical year, month and date from which data were used for this model date. I created hour codes by combining two digits each for the study period, month and hour of day, one digit for the historical year the data were drawn from, and two digits for the day of the month when the historical data were measured.

NOTE: The tabular files shown here are miniaturized examples, much smaller than the ones used for the analysis described in this dissertation. They are intended only to show the layout and type of data included in each table. Complete data files are available by request.

ampl.tab 1 5

<table>
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<tr>
<th>hour</th>
<th>period</th>
<th>date</th>
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<th>hour_of_day</th>
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<td>22030723</td>
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<td>12</td>
</tr>
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<td>2022</td>
<td>22030723</td>
<td>8928</td>
<td>7</td>
<td>18</td>
</tr>
</tbody>
</table>
A.2.4 load_zones.tab

This lists all the load zones in the system, as well as their x and y coordinates in meters (in this case using a UTM-11 projection, but any reasonably distance-preserving projection will work).

<table>
<thead>
<tr>
<th>load_zone</th>
<th>load_zone_x</th>
<th>load_zone_y</th>
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</thead>
<tbody>
<tr>
<td>Orange</td>
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<td>3742485</td>
</tr>
<tr>
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<td>924704</td>
<td>3786044</td>
</tr>
<tr>
<td>Other_SCE</td>
<td>1025381</td>
<td>3930264</td>
</tr>
</tbody>
</table>

A.2.5 trans_lines.tab

This describes all existing or potential transmission corridors, and shows the existing transfer capability from the start to the end, and to the start from the end.

<table>
<thead>
<tr>
<th>load_zone_start</th>
<th>load_zone_end</th>
<th>tid</th>
<th>transmission_length_km</th>
<th>transmission_efficiency</th>
<th>existing_transmission_from</th>
<th>existing_transmission_to</th>
</tr>
</thead>
<tbody>
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<td>193.598794895526</td>
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</tbody>
</table>

A.2.6 system_load.tab

This file lists all the hourly loads in each load zone (in megawatts).

<table>
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<th>hour</th>
<th>system_load</th>
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</thead>
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<td>City</td>
<td>Date</td>
<td>System Load</td>
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<td>-------------</td>
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This describes the capabilities and locations of all existing power plants.

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<th>max_age</th>
<th>overnight_cost</th>
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<th>variable_o_m</th>
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This describes the location and time-varying flow limits of simple and pumped hydro plants.

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A.2.9 connect_cost.tab

This shows the project-specific costs of connecting each new power plant to the existing transmission network. These are added to the generic connection costs for each technology shown in generator_cost.dat (usually costs are given in only one of these locations).

A.2.10 max_capacity.tab

For new power plants that can only be built in limited amounts in each location (e.g., wind farms), this shows the maximum capacity at each location. Technologies represented here should also have their “resource_limited” flag set in generator_costs.dat.

A.2.11 cap_factor.tab

This shows the hourly performance of new intermittent power plants.
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</tbody>
</table>
This optional file describes a stepwise demand curve for electricity. To use it, you will need to use commands like this after running windsun.run and before solving the model:

```
update data;
data elastic_demand.dat;
```

```
elastic_demand.dat
```

```
# Stepwise demand curve for electricity on an annual time scale.
# The first and last breakpoints show the minimum and maximum possible
# annual demand (as a fraction of base-case year round power consumption in each zone).
# Between those is shown the power price that would induce each level of demand
# (or, equivalently, the value of additional power when the supply is at each level).
# The power prices are expressed as fractions of a base-case price in each zone.
# The price levels are assumed to apply to the _right_ of each breakpoint.
# The last price level is ignored, because it is to the right of the highest allowed load.
# To use a fixed power demand, use the model's default values (one breakpoint with a quantity and price of 1).

param:
  ANNUAL_DEMAND_BREAKPOINTS:
    annual_demand_quantity_vs_base  annual_demand_price_vs_base :=
1  0.74  1.666666667
2  0.76  1.615384615
3  0.78  1.564102564
4  0.80  1.512820513
5  0.82  1.461538462
6  0.84  1.41025641
7  0.86  1.358974359
8  0.88  1.307692308
9  0.90  1.256410256
10 0.92  1.205128205
11 0.94  1.153846154
12 0.96  1.102564103
13 0.98  1.051282051
14 1.00  0.948717949
15 1.02  0.897435897
16 1.04  0.846153846
17 1.06  0.794871795
18 1.08  0.743589744
19 1.10  0.692307692
20 1.12  0.641025641
21 1.14  0.58974359
22 1.16  0.538461538
23 1.18  0.487179487
24 1.20  0.435897436
25 1.22  0.384615385
26 1.24  0.333333333
;

# base prices for demand curve for each load zone
# note: these prices can be found by running the model for a base year (e.g., 2005)
# with no reserve margin, no option to build new plants, transmission or local T&D, no plant retirements
```
A.3 Utility Scripts

These scripts are useful for running the model repeatedly or recording output from the model.

A.3.1 load.run

This is a shorthand script for loading the model when ampl is already focused on a particular data directory. It saves a few characters of typing, and is symmetrical with “go.run”.

<data file directory>/load.run

```plaintext
include ../windsun.run;
```

A.3.2 go.run

This is a shorthand script for solving the model and displaying information about the solution. Usually the model is run via the following commands:

cd <data file directory>;

```plaintext
<data file directory>/load.run
```
This script shows rudimentary information about the performance of the proposed investments during the final study period. (It should be run after the model has been solved.)

```
print "lnTax=\%d: cost=\$\%3.2f/MWh, final wind/solar=\%2d\%, geothermal=\%2d\%, nuclear=\%2d\%, coal=\%2d\%/ln\",
carbon_cost,
(Power_Cost - (0 + sum {(z, t, s, o) in PROJ_DISPATCH, h in HOURS}
   DispatchGen[z, t, s, o] * (carbon_cost_per_mwh[t, h])
 + sum {(z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p}
   OperateEPDuringYear[z, e, p]
   * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e]
   * (ep_carbon_cost_per_mwh[z, e, h])
 + sum {(z, e, h) in EP_DISPATCH_HOURS}
   DispatchEP[z, e, h]
   * (ep_carbon_cost_per_mwh[z, e, h])
)) / system_load_discounted,
100*(sum {(z, t, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS: period[h]=last(PERIODS)}
(1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v] * hours_in_sample[h])
/ (sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} (system_load_fixed[z,h] +
DispatchSystemLoad[z,h]) * hours_in_sample[h]),
# hydro
(sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} hours_in_sample[h] * (}
# pumped hydro, de-rated to reflect occasional unavailability of the hydro plants
+ (1 - forced_outage_rate_hydro) * (sum {(z, s) in PROJ_PUMPED_HYDRO} DispatchPumpedHydro[z, s, h])
- (1 - forced_outage_rate_hydro) * (1/pumped_hydro_efficiency) *
(sum {(z, s) in PROJ_PUMPED_HYDRO} StorePumpedHydro[z, s, h])
# simple hydro, dispatched using the season-hour schedules chosen above
# also de-rated to reflect occasional unavailability
+ (1 - forced_outage_rate_hydro) *
(min_hydro_dispatch_all_sites[z, date[h]]
 + HydroDispatchShare[period[h], z, season_of_year[h], hour_of_day[h]]
```

```
* (avg_hydro_dispatch_all_sites[z, date[h]] - min_hydro_dispatch_all_sites[z, date[h]]) * 24)
)) * 100 / (sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} (system_load_fixed[z,h] +
DispatchSystemLoad[z,h]) * hours_in_sample[h]),
# geothermal
(sum {(z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=last(PERIODS) and ep_fuel[z, e]="Geothermal"}
(OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) *
ep_size_mw[z, e] * hours_in_sample[h])
* 100 / (sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} (system_load_fixed[z,h] +
DispatchSystemLoad[z,h]) * hours_in_sample[h]),
# nuclear
(sum {(z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=last(PERIODS) and ep_fuel[z, e]="Nuclear"}
(OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) *
ep_size_mw[z, e] * hours_in_sample[h])
* 100 / (sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} (system_load_fixed[z,h] +
DispatchSystemLoad[z,h]) * hours_in_sample[h]),
# coal
(sum {(z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=last(PERIODS) and ep_fuel[z, e]="Coal"}
(OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) *
ep_size_mw[z, e] * hours_in_sample[h])
* 100 / (sum {z in LOAD_ZONES, h in HOURS: period[h]=last(PERIODS)} (system_load_fixed[z,h] +
DispatchSystemLoad[z,h]) * hours_in_sample[h]);
```
A.3.4 carbon_curve.run

This script runs the model repeatedly with different carbon costs, saves the binary solution files, and exports text files describing the components and cost of the optimal system at each carbon cost. It should be invoked from within the <data file directory> via “include ../carbon_curve.run;”.

carbon_curve.run

include load.run;

# choose an output file, so we know the name of the file being stored:
# random, to avoid conflict with other solutions running at the same time
option randseed "";
option outopt ("bamplsol_" & gsub(scenario_name, "/", ".") & "." & round(Uniform(0, 1000000), 0));

if match($cplex_options, “optimality”) = 0 then
    option cplex_options ($cplex_options & " optimality=1e-5");
;
# read in the previously stored solution
solution sol_gen_trans_0.sol;

let CARBON_COSTS := 0 .. 200 by 10;
for {c in CARBON_COSTS} {
    let carbon_cost := c;
    let curtime := time();
    write;   # save the solution each time, so it can be restored and copied
    solve;

    # show some info about this run
    printf "%d seconds to solve.", time() - curtime;
    include ../basicstats.run;

    # lock in all current decisions, other than transmission dispatch,
    # and then try to reduce transmission usage as much as possible.
    # This ensures that any surplus power gets counted in the zone where it was generated,
    # rather than moving across to another zone that already has enough.

    # save a copy of the current solution (this will be restored at the end, to speed things along)
    shell ("cp " & substr($outopt, 2) & ".sol results/sol" & carbon_cost & ".sol");

    # fix all variables except non-reserve transmission dispatch
    let curtime := time();
    fix InstallGen;
    fix DispatchGen;
    fix DispatchSystemLoad;
    fix OperateEPDuringYear;
    fix DispatchEP;
fix InstallTrans;
fix DispatchTransTo_Reserve;
fix DispatchTransFrom_Reserve;
fix InstallLocalTD;
fix StorePumpedHydro;
fix DispatchPumpedHydro;
fix StorePumpedHydro_Reserve;
fix DispatchPumpedHydro_Reserve;
fix HydroDispatchShare;
fix HydroDispatchShare_Reserve;
fix AcceptInterruptibleLoad;
fix InterruptibleLoadCost;
fix ClearAnnualDemand;
fix AnnualDemandBenefit;
optimal Transmission_Usage;
option presolve_eps 1e-10;

write;
solve;
# save a copy of this solution
shell("cp " & substr($outopt, 2) & ".sol results/sol" & carbon_cost & "trans.sol");

objective Power_Cost;
unfix InstallGen;
unfix DispatchGen;
unfix DispatchSystemLoad;
unfix OperateEPDuringYear;
unfix DispatchEP;
unfix InstallTrans;
unfix DispatchTransTo_Reserve;
unfix DispatchTransFrom_Reserve;
unfix InstallLocalTD;
unfix StorePumpedHydro;
unfix DispatchPumpedHydro;
unfix StorePumpedHydro_Reserve;
unfix DispatchPumpedHydro_Reserve;
unfix HydroDispatchShare;
unfix HydroDispatchShare_Reserve;
unfix AcceptInterruptibleLoad;
unfix InterruptibleLoadCost;
unfix ClearAnnualDemand;
unfix AnnualDemandBenefit;

printf "%d seconds to re-solve, minimizing transmission use\n", time()-curtime;

let curtime := time();
include ../record_results.run;
printf "time taken to store results: %d seconds\n", time()-curtime;

# restore the original solution
solution ("results/sol" & carbon_cost & "cost.sol");
}
A.3.5 record_results.run

This script records complete details about the behavior and costs of the currently-solved model in standard .csv text files.

record_results.run

# store all hourly generation data in standardized, MW terms
# hourly power production from each source
# as well as total CO2 emissions per hour, heat rate, variable costs per MWh
# It might be better to report sub-components (CO2_per_mwh, variable_o_m and fuel_cost_hourly) instead of total emissions and variable costs
# (that would simplify the code here, but then the components would have to be multiplied and added in mysql later)
let outfile := "results/power_" & carbon_cost & ".csv";
printf "scenario_name,carbon_cost,period,load_area,date,hour,technology,site,orientation,new,baseload,cogen,fuel,power,co2_tons,hours_in_sample,heat_rate,fuel_cost_tot,carbon_cost_tot,variable_o_m_tot"
> (outfile);

# new dispatchable projects
# (21 seconds, 1.5 MB)
printf {(z, t, s, o) in PROJ_DISPATCH, h in HOURS}
"%s,%f,%d,%s,%d,%s,%s,%d,%d,%s,%s,%d,%d,%s,%d,%d,%s,%d,%d,%s,%f,%f,%f,%f,%f,%f
", scenario_name, carbon_cost, period[h], z, date[h], h, t, s, o, 1, 0, 0, fuel[t],
DispatchGen[z, t, s, o, h],
DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * carbon_content[fuel[t]],
hours_in_sample[h],
heat_rate[t],
DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * fuel_cost_hourly[fuel[t], h],
DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * carbon_content[fuel[t]] * carbon_cost,
DispatchGen[z, t, s, o, h] * variable_o_m[t]
>> (outfile);

# new intermittent projects (all renewables, so no carbon emissions)
# (takes 114 seconds, 3 MB)
# note: we only report the total for each zone; totals for each site can be derived directly from the decision variables
printf {(z, t, s, o, v) in PROJ_INTERMITTENT, h in HOURS}
"%s,%f,%d,%s,%d,%s,%d,%s,%s,%d,%d,%s,%s,%d,%d,%s,%s,%d,%d,%s,%d,%d,%s,%d,%d,%s,%f,%f,%f,%f,%f,%f
", scenario_name, carbon_cost, p, z, date[h], h, t, "na", "na", 1, 0, 0, fuel[t],
(sum {(z, t, s, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS}
(1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v]),
0,
hours_in_sample[h],
0,
0,
(sum {(z, t, s, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS}
(1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v]) * variable_o_m[t]
>> (outfile);
# existing baseload plants
# (takes 178 seconds, 6 MB)
printf \{z, e, p \in EP_BASELOAD_PERIODS, h \in HOURS: period[h]=p\}
"%s,%f,%d,%s,%d,%s,%s,%d,%s,%d,%s,%d,%s,%f,%f,%d,%f,%f,%f,%f,%f%n",
scenario_name, carbon_cost, p, z, date[h], h, "na", e, "na", 0, ep_baseload[z, e], ep_cogen[z, e], ep_fuel[z, e],
OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e],
OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e]
  * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]],
hours_in_sample[h],
ep_heat_rate[z, e],
OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e]
  * ep_heat_rate[z, e]/1000 * fuel_cost_hourly[ep_fuel[z, e], h],
OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e]
  * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] * carbon_cost,
-operate_variable_o_m[z, e]
>> (outfile);

# existing dispatchable plants
# (takes 109 seconds, 4 MB)
printf \{z, e, h \in EP_DISPATCH_HOURS, p \in PERIODS: p=period[h]\}
"%s,%f,%d,%s,%d,%d,%s,%s,%s,%d,%d,%s,%f,%f,%d,%f,%f,%f,%f,%f%n",
scenario_name, carbon_cost, p, z, date[h], h, "na", e, "na", 0, ep_baseload[z, e], ep_cogen[z, e], ep_fuel[z, e],
DispatchEP[z, e, h],
DispatchEP[z, e, h] * ep_heat_rate[z, e] * carbon_content[ep_fuel[z, e]] / 1000,
hours_in_sample[h],
ep_heat_rate[z, e],
DispatchEP[z, e, h]
  * ep_heat_rate[z, e]/1000 * fuel_cost_hourly[ep_fuel[z, e], h],
DispatchEP[z, e, h]
  * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] * carbon_cost,
DispatchEP[z, e, h]
  * ep_variable_o_m[z, e]
>> (outfile);

# hydro pumping (6 sec)
printf \{(z, s) \in PROJ_PUMPED_HYDRO, h \in HOURS, p \in PERIODS: period[h]=p\}
"%s,%f,%d,%s,%d,%s,%s,%d,%d,%s,%s,%d,%f,%f,%d,%f,%f,%f,%f%n",
scenario_name, carbon_cost, p, z, date[h], h, "na", s, "na", 0, 0, 0, "Hydro Pumping",
-1 * (1 - forced_outage_rate_hydro) * (1/pumped_hydro_efficiency) * StorePumpedHydro[z, s, h],
0, hours_in_sample[h], 0,
0, 0, 0
>> (outfile);

# hydro dispatch
# (61 s, 6 MB)
printf \{(z, s) \in PROJ_PUMPED_HYDRO, h \in HOURS, p \in PERIODS: period[h]=p\}
"%s,%f,%d,%s,%d,%s,%s,%d,%d,%s,%s,%d,%f,%f,%d,%f,%f,%f,%f%n",
scenario_name, carbon_cost, p, z, date[h], h, "na", s, "na", 0, 0, 0, "Hydro",
(1 - forced_outage_rate_hydro) * DispatchPumpedHydro[z, s, h],
record_results.run

0, hours_in_sample[h], 0,
0, 0, 0
>> (outfile);
printf {z in LOAD_ZONES, h in HOURS, p in PERIODS: period[h]=p}
"%s,%f,%d,%d,%d,%d,%d,%d,%d,%d,%d,%f,%d,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,}
```plaintext
record_results.run

0, hours_in_sample[h], 0,
0, 0, 0
>> (outfile);

printf {z in LOAD_ZONES, h in HOURS, p in PERIODS: period[h]=p}
"%s,%f,%d,%s,%s,%s,%s,%d,%d,%d,%s,%f,%f,%f,%f,%f
",
scenario_name, carbon_cost, p, z, date[h], h, "na", "Price-Induced Load", "na", 0, 0, 0, "na",
ystem_load_fixed[z, h] * (ClearAnnualDemand[z, period[h]]/max(annual_demand_quantity_base_mwh[z, period[h]],
1e-6) - 1),
0, hours_in_sample[h], 0,
0, 0, 0
>> (outfile);

close (outfile);

#########################################################################
# store all gen/trans capacity data in standardized, MW terms
# (these are quoted as total capacity installed up through each study period)

let outfile := "results/gen_cap_" & carbon_cost & ".csv";
printf "scenario_name,carbon_cost,period,load_area,technology,site,"&
"orientation,new,baseload,cogen,fuel,capacity,fixed_cost
" > (outfile);

# new projects (either intermittent or dispatchable)
# (this can be changed to just dispatchable or intermittent by using PROJ_DISPATCH or PROJ_INTERMITTENT
# instead of PROJECTS)
printf {(z, t, s, o) in PROJECTS, p in PERIODS: (max {(z, t, s, o, v) in PROJECT_VINTAGES} InstallGen[z, t, s, o, v]) > 0}
"%s,%f,%d,%s,%s,%s,%s,%d,%d,%s,%f,%f
",
scenario_name, carbon_cost, p, z, t, s, o, 1, 0, 0, fuel[t],
sum {(z, t, s, o, v) in PROJECT_VINTAGES: v <= p < project_end_year[t, v]} InstallGen[z, t, s, o, v],
sum {(z, t, s, o, v) in PROJECT_VINTAGES: v <= p < project_end_year[t, v]} InstallGen[z, t, s, o, v]
* (capital_cost_annual_payment[z,t,s,o,v] + fixed_cost_proj[t,v]) * 1000 * (1-
(1/(1+discount_rate)^(years_per_period))/discount_rate
>> (outfile);

# existing plants (either baseload or dispatchable)
# note: they're only counted as "capacity" if they are operable during this period
# and baseload plants are assumed to be operable only up to 1-ep_scheduled_outage_rate
printf {(z, e, p) in EP_PERIODS}
"%s,%f,%d,%s,%s,%s,%s,%d,%d,%s,%f,%f
",
scenario_name, carbon_cost, p, z, "na", e, "na", 0, ep_baseadow[z, e], ep_cogen[z, e], ep_fuel[z, e],
OperateEPEnteringYear[z, e, p] * ep_size_mw[z, e]
* if ep_baseadow[z, e] then (1-ep_scheduled_outage_rate[z, e]) else 1,
OperateEPJuringYear[z, e, p] * ep_size_mw[z, e] * ep_fixed_cost[z, e, p] * (1+discount_rate)^(p-base_year)
+ ep_size_mw[z, e] * ep_capital_cost_annual_payment[z, e] * 1000 * (1-
(1/(1+discount_rate)^(years_per_period))/discount_rate
>> (outfile);

# hydro plants (pumped or simple)
# note: capacity is defined as the maximum possible output on any date in the period
# updated 9/15/08 to include the same fixed cost for hydro as in the Total_Cost objective function
printf {(z, s) in PROJ_HYDRO, p in PERIODS}
"%s,%f,%d,%s,%s,%s,%s,%d,%d,%s,%f,%f
",
scenario_name, carbon_cost, p, z, "na", s, "Hydro", max {d in DATES, h in HOURS: date[h] = d and period[h] = p} max_hydro_flow[z, s, d].
```
(max {d in DATES, h in HOURS: date[h] = d and period[h] = p} max_hydro_flow(z, s, d)) * hydro_annual_payment_per_mw * (1-(1/(1+discount_rate)^(years_per_period)))/discount_rate
>> (outfile);

## existing transmission capacity into each zone
## note: maximum delivery into each zone is reduced by transmission inefficiency
printf {z in LOAD_ZONES, p in PERIODS}
  "%d,%d,%s,%s,%s,%s,%d,%d,%s,%s%n",
  carbon_cost, p, "na", "Transmission", "na", 0, 0, 0, "na",
  # sum {(z, z2) in TRANS_LINES} transmission_efficiency[z, z2] * existing_transmission[z, z2]
  + sum {(z1, z) in TRANS_LINES} transmission_efficiency[z1, z] * existing_transmission[z1, z]
>> (outfile);

## new transmission capacity into each zone
printf {z in LOAD_ZONES, p in PERIODS}
  "%d,%d,%s,%s,%s,%s,%d,%d,%d,%s,%f%n",
  carbon_cost, p, z, "na", "Transmission", "na", 0, 0, 0, "na",
  sum {(z, z2) in TRANS_LINES} transmission_efficiency[z, z2] * InstallTrans[z, z2, v]
  + sum {(z1, z) in TRANS_LINES} transmission_efficiency[z1, z] * InstallTrans[z1, z, v]
>> (outfile);

close (outfile);

########################
# store all trans capacity between zones
let outfile := "results/trans_cap_" & carbon_cost & ".csv";
printf "scenario_name,carbon_cost,period,start,end,tid,new,trans_mw,fixed_cost
" >> (outfile);

# existing lines
# TODO: update this if the main model is changed to retire existing lines when they reach  
# transmission_max_age_years
# TODO: switch this to record the bidirectional capacities, instead of averaging them together
printf {(z1, z2) in TRANS_LINES, p in PERIODS}:
  "%s,%f,%d,%s,%s,%d,%f,%f%n",
  scenario_name, carbon_cost, p, z1, z2, tid[z1, z2], 0, (existing_transmission_from[z1, z2]+existing_transmission_to[z1, z2])/2,
  (existing_transmission_from[z1, z2]+existing_transmission_to[z1, z2])/2
  * transmission_annual_payment[z1, z2, first(PERIODS)] * (1-(1/(1+discount_rate)^(years_per_period)))/discount_rate
>> (outfile);

# new lines
printf {(z1, z2) in TRANS_LINES, p in PERIODS}:
  "%s,%f,%d,%s,%s,%d,%f,%f%n",
  scenario_name, carbon_cost, p, z1, z2, tid[z1, z2], 1, sum {v in VINTAGE_YEARS: v <= p < transmission_end_year[v]} InstallTrans[z1, z2, v],
  (sum {v in VINTAGE_YEARS: v <= p < transmission_end_year[v]} InstallTrans[z1, z2, v] * 
  transmission_annual_payment[z1, z2, v]) * (1-(1/(1+discount_rate)^(years_per_period)))/discount_rate
>> (outfile);

close (outfile);
# store local T&D capacity within each zone

```plaintext
let outfile := "results/local_td_cap_" & carbon_cost & ".csv";
printf "scenario_name,carbon_cost,period,load_area,local_td_mw,localTd_fixed_cost\n" >> (outfile);
```

```plaintext
printf (p in PERIODS, z in LOAD_ZONES):
  "\%s,\%f,\%d,\%s,\%f,\%f\n",
  scenario_name, carbon_cost, p, z,
  sum {v in VINTAGE_YEARS: v <= p < transmission_end_year[v]} InstallLocalTD[z, v],
  (sum {v in VINTAGE_YEARS: v <= p < transmission_end_year[v]} InstallLocalTD[z, v]) * local_td_annual_payment_per_mw * (1-(1/(1+discount_rate)^(years_per_period))/discount_rate
>> (outfile);
```

```plaintext
close (outfile);
```

## A.3.6 marginal_solar_curve.run

This script runs the model repeatedly, forcing it to use increasing shares of solar power, and
recording total power production and total cost in various categories at each step. The dif-
erence between these values at successive steps can be used to calculate the marginal costs
and marginal benefits per megawatt hour of power. The script can also be used, with minor
changes, for wind farms.

```plaintext
marginal_solar_curve.run
```

```plaintext
print "Loading model..."
include load.run;
let carbon_cost := 30;
print "Reading original solution...";
#solution results/sens_full_model_24_hours_x_2_days_x_12_months_30_cost.sol;
solution results/sens_base_case_30_cost.sol;
print "Finished reading original solution."

# fix investments in all renewables except solar.
# these are held constant so the effect of solar on gas plant investment is more obvious
fix {(z, t, s, o, v) in PROJECT_VINTAGES: carbon_content[fuel[t]] = 0 and t != tech_trough} InstallGen[z, t, s, o, v];

# also fix decisions about running or not running existing plants,
# since those would make graphing very tricky (there could be discontinuities,
# where an existing plant shuts down, and there’s a jump up in capital costs
# to replace it with a new gas plant, and a jump down in fuel costs
fix OperateEPDuringYear;

# fix decisions about interruptible load and demand elasticity, for similar reasons
fix AcceptInterruptibleLoad;
fix InterruptibleLoadCost;
fix ClearAnnualDemand;
fix AnnualDemandBenefit;
```
marginal_solar_curve.run

# add a constraint that we must reach a certain MW target for solar
param target_mw default 0;
subject to Resource_Target:
   sum {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS: t=tech_trough} InstallGen[z, t, s, o, v] = target_mw;

let outfile := "results/marginal_solar_curve_"&carbon_cost&".csv";

# read existing solution, or start a new curve
if 1=1 then {
   print "Reading saved solution...";
   solution results/sol_30_30000_mw_trough_cost.sol;
} else {
   print "target_mw,capacity_trough,capacity_nontrough,trans_mw_km,fixed_cost_trough,fixed_cost_nontrough,"
   "variable_cost,carbon_cost,trans_cost,local_td_cost,trough_mwh,surplus_mwh"
   > (outfile);
}

for {cur_target in 31000 .. 60000 by 1000} {
   let target_mw := cur_target;
   option solution_file_stem ("results/sol_" & carbon_cost & "_" & round(cur_target, 10) & "_mw_trough");

   let curtime := time();
   print "Finding minimum-cost solution, target=%f...\n", round(cur_target, 10);
   write ("b" & $solution_file_stem & ".nl");
   solve;
   shell "date"; # show current time, for cross-referencing later if needed
   print "target=%f, %d seconds to re-solve.\n", cur_target, time() - curtime;
   remove ($solution_file_stem & ".nl");

   # print "Reading saved solution, cur_target=%f...\n", round(cur_target, 10);
   # solution ($solution_file_stem & ".sol");
   # print "Finished reading saved solution.\n";

   # fix all the other variables except transmission
   fix InstallGen;
   fix DispatchGen;
   fix DispatchSystemLoad;
   # fix OperateEPDuringYear; -- already done above
   fix DispatchEP;
   fix InstallTrans;
   # fix DispatchTransTo; -- these are what we want to minimize
   # fix DispatchTransFrom;
   fix DispatchTransTo_Reservation;
   fix DispatchTransFrom_Reservation;
   fix InstallLocalTD;
   fix StorePumpedHydro;
   fix DispatchPumpedHydro;
   fix StorePumpedHydro_Reservation;
   fix DispatchPumpedHydro_Reservation;
   fix HydroDispatchShare;
   fix HydroDispatchShare_Reservation;
   # fix AcceptInterruptibleLoad; -- already done above
#fix InterruptibleLoadCost;
#fix ClearAnnualDemand;
#fix AnnualDemandBenefit;

objective Transmission.Usage;
option presolve_eps 1e-10;

let curtime := time();
printf "Finding minimum-transmission solution, target=%f...\n", round(cur_target, 10);
write ("b" & $solution_file_stem & ".trans");
solve;
shell "date";  # show current time, for cross-referencing later if needed
# show some info about this run
printf "target=%f, %d seconds to re-solve.\n", cur_target, time() - curtime;
# include ../basicstats.run;
remove ($solution_file_stem & ".trans.nl");

objective Power.Cost;

unfix InstallGen;
# keep other renewables fixed
fix {(z, t, s, o, v) in PROJECT_VINTAGES: carbon_content[fuel[t]] = 0 and t != tech_trough} InstallGen[z, t, s, o, v];
unfix DispatchGen;
unfix DispatchSystemLoad;
# unfix OperateEPDuringYear; -- already done above
unfix DispatchEP;
unfix InstallTrans;
#unfix DispatchTransTo; -- these are what we want to minimize
#unfix DispatchTransFrom;
unfix DispatchTransTo_Reserve;
unfix DispatchTransFrom_Reserve;
unfix InstallLocalTD;
unfix StorePumpedHydro;
unfix DispatchPumpedHydro;
unfix StorePumpedHydro_Reserve;
unfix DispatchPumpedHydro_Reserve;
unfix HydroDispatchShare;
unfix HydroDispatchShare_Reserve;
#unfix AcceptInterruptibleLoad; -- already done above
#unfix InterruptibleLoadCost;
#unfix ClearAnnualDemand;
#unfix AnnualDemandBenefit;

# (continued on next page)
marginal_solar_curve.run

# note: these numbers are only meaningful as differences between cases,
# and are given as discounted totals across the whole study.
# Also note: power production is reported in "discounted MWh",
# so that the discounted costs can be divided by the MWh's to get costs and benefits per MWh,
# averaged over the whole study.
printf "%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,%-10.6f,\n",
cur_target,
sum {\{z, t, s, o, v\} in PROJECT_VINTAGES: t = tech_trough} InstallGen[z, t, s, o, v],
sum {\{z, t, s, o, v\} in PROJECT_VINTAGES: t != tech_trough} InstallGen[z, t, s, o, v],
sum {\{z1, z2\} in TRANS_LINES, v in VINTAGE_YEARS} InstallTrans[z1, z2, v] * transmission_length_km[z1, z2],
sum {\{z, t, s, o, v\} in PROJECT_VINTAGES: t = tech_trough} InstallGen[z, t, s, o, v] * fixed_cost[z, t, s, o, v],
sum {\{z, t, s, o, v\} in PROJECT_VINTAGES: t != tech_trough} InstallGen[z, t, s, o, v] * fixed_cost[z, t, s, o, v],
sum {\{z, t, s, o\} in PROJ_DISPATCH, h in HOURS} DispatchGen[z, t, s, o, h] * variable_cost[t, h] + sum {\{z, e, h\} in EP_DISPATCH_HOURS} DispatchEP[z, e, h] * ep_variable_cost[z, e, h],
sum {\{z, t, s, o\} in PROJ_DISPATCH, h in HOURS} DispatchGen[z, t, s, o, h] * carbon_cost_per_mwh[t, h] + sum {\{z, e, h\} in EP_DISPATCH_HOURS} DispatchEP[z, e, h] * ep_carbon_cost_per_mwh[z, e, h],
sum {\{z1, z2\} in TRANS_LINES, v in VINTAGE_YEARS} InstallTrans[z1, z2, v] * transmission_cost_per_mw[z1, z2, v],
sum {z in LOAD_ZONES, v in VINTAGE_YEARS} InstallLocalTD[z, v] * local_td_cost_per_mw[v],
sum {\{z, t, s, o, v, h\} in PROJ_INTERMITTENT_VINTAGE_HOURS: t = tech_trough} hourly_cost_weight[h] * (1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v],
sum {z in LOAD_ZONES, h in HOURS} hourly_cost_weight[h] * Satisfy_Load[z, h].slack
>> (outfile);

# go back to the original solution
solution ($solution_file_stem & ".cost.sol")
}
close (outfile);

A.3.7 Sensitivity Studies

These scripts are used to run sensitivity studies with the model, save the solutions, and record the results in aggregated form. This framework is sometimes easier to use than carbon_curve.run (even for a simple carbon curve) because these scripts dynamically check whether a previous solution has already been saved, and they report results on a more aggregated basis than carbon_curve.run, which makes it easier to inspect and graph results.
A.3.7.1 Sensitivity Cases

These scripts adjust the model and run individual sensitivity cases. They are a useful example of how the model can be adjusted for different conditions.

sens_base_case.run

```plaintext
# base case
# for this particular case, the name must be "base case" and the value must be blank.
# this is then renamed and copied in as the center point for a bunch of other sensitivities later
option sensitivity_name "base case";
option sensitivity_value "";
include ..sensitivity_create_output_file.run;
include load.run;
include ..sensitivity_add_carbon_curve_to_output_file.run;
include ..sensitivity_close_output_file.run;
```

sens_fuel_cost.run

```plaintext
# fuel cost
option sensitivity_name "fuel cost";
include ..sensitivity_create_output_file.run;
include load.run;

param fuel_cost_orig {YEARS, FUELS};
let {y in YEARS, f in FUELS} fuel_cost_orig[y, f] := fuel_cost[y, f];

for {step in {0.5 .. 1.5 by 0.5}} {
    option sensitivity_value (sprintf("%d% of base case fuel cost", step*100));
    let {y in YEARS, f in FUELS} fuel_cost[y, f] := fuel_cost_orig[y, f] * step;
    if step = 1 then {
        include ..sensitivity_add_base_case_to_output_file.run;
    } else {
        include ..sensitivity_add_carbon_curve_to_output_file.run;
    }
}
include ..sensitivity_close_output_file.run;
```
sens_generator_cost.run

# generator cost

option sensitivity_name "generator cost";
include ../sensitivity_create_output_file.run;

include load.run;
# store the best-estimate rates of change
param overnight_cost_change_orig {TECHNOLOGIES};
let {t in TECHNOLOGIES} overnight_cost_change_orig[t] := overnight_cost_change[t];
param fixed_o_m_change_orig {TECHNOLOGIES};
let {t in TECHNOLOGIES} fixed_o_m_change_orig[t] := fixed_o_m_change[t];
param variable_o_m_change_orig {TECHNOLOGIES};
let {t in TECHNOLOGIES} variable_o_m_change_orig[t] := variable_o_m_change[t];

for {step in {0 .. 2 by 0.5}} {
  option sensitivity_value (sprintf("%d\% of base case technological progress", step*100));
  let {t in TECHNOLOGIES} overnight_cost_change[t] := overnight_cost_change_orig[t] * step;
  let {t in TECHNOLOGIES} fixed_o_m_change[t] := fixed_o_m_change_orig[t] * step;
  let {t in TECHNOLOGIES} variable_o_m_change[t] := variable_o_m_change_orig[t] * step;

  if step = 1 then {
    include ../sensitivity_add_base_case_to_output_file.run;
  } else {
    include ../sensitivity_add_carbon_curve_to_output_file.run;
  }

  # print $sensitivity_value;
  # display overnight_cost_change, fixed_o_m_change, variable_o_m_change;
}
include ../sensitivity_close_output_file.run;

sens_transmission_cost.run

# transmission cost

option sensitivity_name "transmission cost";
include ../sensitivity_create_output_file.run;

include load.run;
# save the base-case transmission cost
param transmission_cost_per_mw_km_orig default transmission_cost_per_mw_km;

for {step in {0.7, 1, 1.5, 3}} {
  let transmission_cost_per_mw_km := step * transmission_cost_per_mw_km_orig;
  option sensitivity_value (sprintf("$%d/MW-km transmission cost", transmission_cost_per_mw_km));

  if step = 1 then {
    include ../sensitivity_add_base_case_to_output_file.run;
  } else {

include ../sensitivity_add_carbon_curve_to_output_file.run;
}
# print $sensitivity_name & ": " & $sensitivity_value;
}

let transmission_cost_per_mw_km := transmission_cost_per_mw_km_orig;
# use a trick to increase the cost of new inter-zonal transmission too far to be done:
let {{z1, z2} in TRANS_LINES}
  transmission_length_km[z1, z2] := transmission_length_km[z1, z2] * 1e20;
option sensitivity_value
  (sprintf("$%d/MW-km for new plants, no new inter-zonal transmission", transmission_cost_per_mw_km));
include ../sensitivity_add_carbon_curve_to_output_file.run;

include ../sensitivity_close_output_file.run;

include ..sensitivity_close_output_file.run;

# transfer capability
# store original values
param existing_transmission_from_orig {{z1, z2} in TRANS_LINES}
  default existing_transmission_from[z1, z2];
param existing_transmission_to_orig {{z1, z2} in TRANS_LINES}
  default existing_transmission_to[z1, z2];
# note: it would be nice also to change the transfer capability of
# new lines (which is sort of possible via transmission_cost_per_mw_km),
# but this also changes the cost of connecting projects to the grid,
# which would muddy the analysis, so I leave it alone.

for {step in {0.3, 0.15, 0}} {
  option sensitivity_value (sprintf("%d% de-rating of transfer capability", step*100));
  let {{z1, z2} in TRANS_LINES}
    existing_transmission_from[z1, z2] := (1-step) * existing_transmission_from_orig[z1, z2];
  let {{z1, z2} in TRANS_LINES}
    existing_transmission_to[z1, z2] := (1-step) * existing_transmission_to_orig[z1, z2];
  if step = 0 then {
    include ../sensitivity_add_base_case_to_output_file.run;
  } else {
    include ../sensitivity_add_carbon_curve_to_output_file.run;
  }
  # print $sensitivity_name & ": " & $sensitivity_value;
  # display sum {{z1, z2} in TRANS_LINES} existing_transmission_from[z1, z2];
  # display sum {{z1, z2} in TRANS_LINES} existing_transmission_to[z1, z2];
} include ../sensitivity_close_output_file.run;
# long-term study
# (8 study periods instead of 4, with identical conditions in the second half)

option sensitivity_name "long term study";
include ../sensitivity_create_output_file.run;

option sensitivity_value "4 study periods (16 years)";
include ../sensitivity_add_base_case_to_output_file.run;

option sensitivity_value "8 study periods (32 years)";
cd ../mini_long;
include load.run;

# use a better construction constraint that allows rebuilding after plants retire
delete Maximum_Resource;
subject to Maximum_Resource {(z, t, s, o) in PROJ_RESOURCE_LIMITED, p in PERIODS}:
  sum {(z, t, s, o, v) in PROJECT_VINTAGES: v <= p < project_end_year[t, v]} InstallGen[z, t, s, o, v]
  <= max_capacity[z, t, s, o];
include ../sensitivity_add_carbon_curve_to_output_file.run;

option sensitivity_value "8 study periods with costs frozen after 4th period";

# freeze capital costs after the last period of the first half
redeclare param capital_cost_proj {(z, t, s, o) in PROJECTS, v in VINTAGE_YEARS} =
  overnight_cost[t] * (1+overnight_cost_change[t])
  ^ (min(v, member(floor(card(VINTAGE_YEARS)/2), VINTAGE_YEARS)) - min_vintage_year[t])
  + connect_length_km[z, t, s, o] * transmission_cost_per_mw_km / 1000
  + connect_cost_per_kw_generic[t]
  + connect_cost_per_kw[z, t, s, o]
;
include ../sensitivity_add_carbon_curve_to_output_file.run;

# close the results file
include ../sensitivity_close_output_file.run;

# note: this could leave ampl in the wrong directory,
# but it's not a problem if it's invoked from the shell.

# plant retirement dates

option sensitivity_name "plant retirement dates";
include ../sensitivity_create_output_file.run;
sens_elastic_demand.run

include load.run;

option sensitivity_value ("base case");
include ../sensitivity_add_base_case_to_output_file.run;

option sensitivity_value ("no retirements before ", & member(2, PERIODS));
let {{z, e} in EXISTING_PLANTS: ep_end_year[z, e] < member(2, PERIODS)}
    ep_end_year[z, e] := member(2, PERIODS);
include ../sensitivity_add_carbon_curve_to_output_file.run;

for {step in {1 .. 3}} {
    option sensitivity_value (sprintf("extend plant life by %d years", step * 4));
    let {{z, e} in EXISTING_PLANTS} ep_end_year[z, e] := ep_end_year[z, e] + 4;
    include ../sensitivity_add_carbon_curve_to_output_file.run;

    # print $sensitivity_name : $sensitivity_value;
}
include ../sensitivity_close_output_file.run;

sens_elastic_demand.run

############################################################
# elastic demand
############################################################
option sensitivity_name "elastic demand";
include ../sensitivity_create_output_file.run;
option sensitivity_value "inelastic annual demand";
include ../sensitivity_add_base_case_to_output_file.run;
include load.run;

for {step in {0.5, 1, 2}} {
    update data;
    data ../elastic_demand.dat;  # start with the best-estimate demand curve
    # change the slope of the demand curve by stretching the prices
    # closer or further to 100% of the base price
    # (this lets us keep simple bounds on the quantity, while changing the price range)
    let {bp in ANNUAL_DEMAND_BREAKPOINTS}
        annual_demand_price_vs_base[bp] := (annual_demand_price_vs_base[bp] - 1) / step + 1;
    option sensitivity_value (sprintf("%4.2f elasticity of annual demand", 
        round(  
            (annual_demand_quantity_vs_base[member(2, ANNUAL_DEMAND_BREAKPOINTS)]  
                - annual_demand_quantity_vs_base[member(1, ANNUAL_DEMAND_BREAKPOINTS)])  
            / (annual_demand_price_vs_base[member(2, ANNUAL_DEMAND_BREAKPOINTS)]  
                - annual_demand_price_vs_base[member(1, ANNUAL_DEMAND_BREAKPOINTS)]),  
        2)));
    include ../sensitivity_add_carbon_curve_to_output_file.run;
}
include ../sensitivity_close_output_file.run;
# energy efficiency

```plaintext
option sensitivity_name "energy efficiency";
include ../sensitivity_create_output_file.run;

include load.run;

option sensitivity_value ("base case");
include ../sensitivity_add_base_case_to_output_file.run;

# save the base-case system load
param system_load_fixed_orig {z in LOAD_ZONES, h in HOURS} default system_load_fixed[z,h];

# use the (somewhat) elastic demand curve for efficiency cases
update data:
data ../high_efficiency_demand_curve.dat;
print "Using elastic demand curve:";
display annual_demand_quantity_vs_base, annual_demand_price_vs_base;

for {step in {0, 0.10, 0.20, 0.30, 0.40}} {
    option sensitivity_value (sprintf("%d\% reduction in base-case demand by %d", step * 100, last(PERIODS)));  
    # apply the specified reduction to the demand, phasing it in over the course of the study
    let {z in LOAD_ZONES, h in HOURS} system_load_fixed[z,h] :=
        system_load_fixed_orig[z,h] * (1 - step*ord(period[h], PERIODS)/card(PERIODS));
    include ../sensitivity_add_carbon_curve_to_output_file.run;
    
    # print $sensitivity_name & ": " & $sensitivity_value;
}
include ../sensitivity_close_output_file.run;

# remove the new parameter
delete system_load_fixed_orig;
```

# interruptible load

```plaintext
option sensitivity_name "interruptible load";
include ../sensitivity_create_output_file.run;
option sensitivity_value "no interruptible load";
include ../sensitivity_add_base_case_to_output_file.run;

include load.run;
let interruptible_load_max_share := 0.05;
let interruptible_load_cost_segment_count := 20;
for {step in 0.5 .. 1.5 by 0.5} {
    let interruptible_load_cost_per_kw_year_per_percent_peak_load := step * 19;
```
option sensitivity_value("0-" & round(interruptible_load_max_share*100) & "% interruptible load" & sprintf(" for $0-$%4.2f/kW-year", round(interruptible_load_max_share * interruptible_load_cost_per_kw_year_per_percent_peak_load * 100, 2)));

include ../sensitivity_add_carbon_curve_to_output_file.run;

include ../sensitivity_close_output_file.run;
option sensitivity_value "only solar, concentrated at one site";
include load.run;

subject to One_Trough
{(z, t, s, o, v) in PROJECT_VINTAGES:
   intermittent[t] and not (t=tech_trough and s='Owens__183_tr')):
   InstallGen[z, t, s, o, v] = 0;
include ../sensitivity_add_carbon_curve_to_output_file.run;

# close the results file
include ../sensitivity_close_output_file.run;

# high renewables
# (more wind sites, reduced load, PHEVs, optimal charging of PHEVs)

option sensitivity_name "high renewables";
include ../sensitivity_create_output_file.run;
option sensitivity_value "base case";
#include ../sensitivity_add_base_case_to_output_file.run;
include load.run;

# more wind resources
option sensitivity_value "2x more wind";
let {(z, t, s, o) in PROJ_RESOURCE_LIMITED: t=tech_wind}
   max_capacity[z, t, s, o] := max_capacity[z, t, s, o] * 2;
include ../sensitivity_add_carbon_curve_to_output_file.run;

# temporary, simplified calculation of how much reschedulable load to use.
# in this case, it is an average of 10500 MW on every day in 2022,
# which is distributed among load zones proportional to their existing electricity load.
# It is ramped up from 0% of this level in 2010 to 100% in 2022.
# note: there is no easy way to figure out the period for a particular date, so I use an undocumented
# approach that will break if I ever change my date coding strategy or date range!
# TODO: parameterize this, using external data (e.g., precalculate the moveable load for every zone and date)
param zone_load_share {z in LOAD_ZONES} =
   (sum {h in HOURS} system_load_fixed[z, h]*hours_in_sample[h])
   / (sum {z1 in LOAD_ZONES, h in HOURS} system_load_fixed[z1, h] * hours_in_sample[h]);
param car_load {d in DATES} = (10500 * floor(d/1e6 - 10)/12);
option sensitivity_value "uniformly charged PHEVs";
let {z in LOAD_ZONES, h in HOURS, d in DATES : date[h]=d}
   system_load_fixed[z, h] := system_load_fixed[z, h] + car_load[d] * zone_load_share[z];
include ../sensitivity_add_carbon_curve_to_output_file.run;

option sensitivity_value "optimally charged PHEVs";
# undo the previous change to fixed system loads
let {z in LOAD_ZONES, h in HOURS, d in DATES : date[h]=d}
   system_load_fixed[z, h] := system_load_fixed[z, h] - car_load[d] * zone_load_share[z];
# add moveable load instead

```plaintext
let {z in LOAD_ZONES, d in DATES}
  system_load_moveable[z, d] := car_load[d] * zone_load_share[z];
include ../sensitivity_add_carbon_curve_to_output_file.run;

option sensitivity_value "20% demand reduction";
option sensitivity_record_detailed_results 1;
# reduce base-case demand by by 0-20% over the course of the study,
# with a relatively inelastic demand curve.
update data;
data ../high_efficiency_demand_curve.dat;
let {z in LOAD_ZONES, h in HOURS} system_load_fixed[z,h] :=
  system_load_fixed[z,h] * (1 - 0.2 * ord(period[h], PERIODS)/card(PERIODS));
include ../sensitivity_add_carbon_curve_to_output_file.run;
option sensitivity_record_detailed_results 0;

# close the results file
include ../sensitivity_close_output_file.run;
```

### A.3.7.2 Supporting Scripts

These scripts are called by the ones above to record the results of each sensitivity study.

```plaintext
sensitivity_create_output_file.run

# prepare a file to hold the case-by-case results

# note: these are stored in a subdirectory of the model root
# (rather than in subdirectories of individual scenarios),
# so that different scenarios can be loaded and written as
# different ends of the same sensitivity analysis.

# All sensitivity parameters are stored as ampl options
# (environment variables), so that they will persist even if
# the model is loaded, reset, etc.

# choose a suitable name for this sensitivity analysis
option sensitivity_outfile (  
  "./sensitivity/sens_" & gsub($sensitivity_name, "[^a-zA-Z0-9-\-]", "_")
  & ".csv");

# also record the name for the base-case results file
option sensitivity_basefile "./sensitivity/sens_base_case.csv";

print
  ("sensitivity_name,sensitivity_value,period,carbon_cost,"
  & "co2_tons,total_cost,total_carbon_cost,"
  & "load_mwh,gen_mwh,"
  & "gen_wind,gen_trough,gen_pv,gen_geothermal,gen_hydro,gen_nuclear,gen_gas,gen_coal"
  & "\n") > ($sensitivity_outfile);
```
sensitivity_add_carbon_curve_to_output_file.run

# before calling this script, you should have a model open and ready to solve (or solved)
# you should also set these settings, which are used to label the solution files and results
# option sensitivity_name
# option sensitivity_value
# you should also call ../sensitivity_create_output_file.run,
# which will create a file with appropriate header and store its name for ../sensitivity_add_row_to_output_file.run.

# you can optionally use this setting to cause this script to call ../record_results.run as well:
# option sensitivity_record_detailed_results 1

option randseed "";

# sometimes cplex's solution from the regular version of the model has variable values
# slightly outside the allowed range, which makes cplex report the problem is infeasible
# when it tries to solve it after these variables are fixed (below). So we set the tolerance
# a little looser, to avoid this problem.
if match($cplex_options, "optimality") = 0 then
  option cplex_options ($cplex_options & " optimality=1e-5");
;

# create some settings to keep track of the name of the solution files,
# and whether they exist already (this can't be done with parameters,
# because that will break any loops that call this file)

option sens_did_no_trans_first_solution 0;

option sens_sol_file_status_file ("readfile_" & round(Uniform(0, 1000000), 0) & ".txt");

option sens_solution_file_stem ("results/sens_" & gsub($sensitivity_name, "[^a-zA-Z0-9-\_]", "_")
  & (if $sensitivity_value="" then "_" & gsub($sensitivity_value, "[^a-zA-Z0-9-\_]", "_") & "_")
  & "_");

let CARBON_COSTS := 0 .. 200 by 10;
for {c in CARBON_COSTS} {
  let carbon_cost := c;
  let curtime := time();

  # check whether the first (cost-oriented) solution file exists
  option sens_solution_file_name ($sens_solution_file_stem & carbon_cost & "_cost.sol");
  remove ($sens_sol_file_status_file);
  shell ('if test -f "$sens_solution_file_name" ; then echo 1 ; else echo 0 ; fi')
  > ($sens_sol_file_status_file);
  read readfile < ($sens_sol_file_status_file);
  remove ($sens_sol_file_status_file);

  if num(readfile) = 1 then {
    print "Using existing solution for sensitivity %s, carbon_cost=%d\n",
    $sensitivity_name & (if $sensitivity_value="" then "_" else " (" & $sensitivity_value & ")"),
    carbon_cost;
    solution ($sens_solution_file_name);
  } else {
    print "Solving for sensitivity %s, carbon_cost=%d\n",
  }
  solution ($sens_solution_file_name);
  if curtime - time() > 1 then {
    print " течение времени",
    time()
  }
}


sensitivity_add_carbon_curve_to_output_file.run

$sensitivity_name & (if $sensitivity_value="" then "" else " ( & $sensitivity_value & ")"), carbon_cost;

# do a two-step solution the first time through, which is faster than solving in one step
if num($sens_did_no_trans_first_solution) = 0 then {
  option sens_did_no_trans_first_solution 1;

  # speed up the first solution by finding a nearby solution without any new transmission
  # also discard any previous solution values, because they are probably from the
  # last carbon curve (with carbon_cost=200) and won't help for this new sensitivity case.
  option reset_initial_guesses 1;
  printf "Finding first solution (no new transmission)\n";
  fix InstallTrans;
  solve;
  unfix InstallTrans;
  # go back to reusing solutions, because it speeds up the carbon curve a lot
  option reset_initial_guesses 0;

  printf "\nFound no-transmission solution for sensitivity %s, carbon_cost=%d.\n",
    $sensitivity_name & (if $sensitivity_value="" then "" else " ( & $sensitivity_value & ")"),
    carbon_cost;
}

write("b" & sub($sens_solution_file_name, ".sol", ""));
solve;
# remove binary file that was created for the solver
remove (sub($sens_solution_file_name, ".sol", ".nl"));

# show some info about this run
printf "\nSensitivity %s, %d seconds to solve.\n",
  $sensitivity_name & (if $sensitivity_value="" then "" else " ( & $sensitivity_value & ")"),
  time() - curtime;
}

# finished loading or creating the cost-oriented solution
include ../basicstats.run;

# next, we have to switch over to a similar solution that minimizes transmission usage
# this way, we can tell when there's surplus power generated, even if the model burns
# it up as losses from spurious transmission by default.

# fix all variables except non-reserve transmission dispatch
let curtime := time();
fix InstallGen;
fix DispatchGen;
fix DispatchSystemLoad;
fix OperateEPDuringYear;
fix DispatchEP;
fix InstallTrans;
fix DispatchTransTo_Reserve;
fix DispatchTransFrom_Reserve;
fix InstallLocalTD;
fix StorePumpedHydro;
fix DispatchPumpedHydro;
fix StorePumpedHydro_Reserve;
fix DispatchPumpedHydro_Reserve;
sensitivity_add_carbon_curve_to_output_file.run

fix HydroDispatchShare;
fix HydroDispatchShare_Reserve;
fix AcceptInterruptibleLoad;
fix InterruptibleLoadCost;
fix ClearAnnualDemand;
fix AnnualDemandBenefit;

objective Transmission_Usage;

# check whether the second (transmission-oriented) solution file exists
option sens_solution_file_name ($sens_solution_file_stem & carbon_cost & "_trans.sol");

remove ($sens_sol_file_status_file);
shell ('if test -f "' & $sens_solution_file_name & '" ; then echo 1 ; else echo 0 ; fi')
> ($sens_sol_file_status_file);
read readfile < ($sens_sol_file_status_file);
remove ($sens_sol_file_status_file);

if num(readfile) = 1 then {
  printf "Using existing minimum-transmission solution for sensitivity %s, carbon_cost=%d.\n";
  $sensitivity_name & (if $sensitivity_value="" then "" else "(" & $sensitivity_value & ")"),
  carbon_cost;
  solution ($sens_solution_file_name);
} else {
  printf "Finding minimum-transmission solution for sensitivity %s, carbon_cost=%d.\n";
  $sensitivity_name & (if $sensitivity_value="" then "" else "(" & $sensitivity_value & ")"),
  carbon_cost;

  write ("b" & sub($sens_solution_file_name, ".sol", ""));
solve;
  # remove binary file that was created for the solver
  remove (sub($sens_solution_file_name, ".sol", ".nl"));

  # show some info about this run
  printf "Sensitivity %s, minimum-transmission, %d seconds to solve.\n";
  $sensitivity_name & (if $sensitivity_value="" then "" else "(" & $sensitivity_value & ")"),
  time() - curtime;
}

# finished loading or creating the cost-oriented solution
include ../basicstats.run;

# go back to the original version of the model
objective Power_Cost;

unfix InstallGen;
unfix DispatchGen;
unfix DispatchSystemLoad;
unfix OperateEPDuringYear;
unfix DispatchEP;
unfix InstallTrans;
unfix DispatchTransTo_Reserve;
unfix DispatchTransFrom_Reserve;
unfix InstallLocalTD;
unfix StorePumpedHydro;
unfix DispatchPumpedHydro;
sensitivity_add_row_to_output_file.run

unfix StorePumpedHydro_Reserve;
unfix DispatchPumpedHydro_Reserve;
unfix HydroDispatchShare;
unfix HydroDispatchShare_Reserve;
unfix AcceptInterruptibleLoad;
unfix InterruptibleLoadCost;
unfix ClearAnnualDemand;
unfix AnnualDemandBenefit;

include ../sensitivity_add_row_to_output_file.run;

# TODO: this should give different names to the output files, depending on which
# sensitivity case is being run. But that requires rewriting record_results.run
# and the mysql import scripts to use that information, so I'm leaving it alone for now.
if num0($sensitivity_record_detailed_results) > 0 then
  commands ../record_results.run;
;
# restore the original solution, to use as a basis for the next carbon cost
  solution (sub($sens_solution_file_name, "trans.sol", "_cost.sol"));
}

sensitivity_add_row_to_output_file.run

# NOTE: this script provides a good example of how to extract aggregated results from the model after it is solved

# year to analyze for sensitivity reports
option sensitivity_period 2022;

# record a row of results in the output file
# this shows total power generation, carbon emissions, etc., for the specified study period

# things to include (all for final study period)
# see header in sensitivity_create_output_file.run
# sens_name
# sens_value
# period
# carbon_cost
# co2_tons
# total_cost
# total_carbon_cost
# load_mwh
# gen_mwh
# wind_mwh
# trough_mwh
# pv_mwh
# hydro_mwh
# geothermal_mwh
# nuclear_mwh
# gas_mwh
# coal_mwh
it would be nice to include these derived values as well, but that gets ugly (giant, repetitious blocks of code)

```
printf "%s,%s,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f,%f
",
"" & gsub($sensitivity_name, "", "") & "",
"" & gsub($sensitivity_value, "", "") & "",
num($sensitivity_period),
carbon_cost,
```

total carbon emissions (stripped-down version of total cost of carbon calculation below)

```
sum {{z, t, s, o) in PROJ_DISPATCH, h in HOURS: period[h]=num($sensitivity_period)) hours_in_sample[h] * (DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * carbon_content[fuel[t]]) + sum {{z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=num($sensitivity_period)) hours_in_sample[h] * (OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e] * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] + sum {{z, e, h) in EP_DISPATCH_HOURS, p in PERIODS: p=period[h] and p=num($sensitivity_period)) hours_in_sample[h] * (DispatchEP[z, e, h] * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]]),
```

total cost of power, including carbon.

```
# these terms are copied piece by piece from record_results.run, with row indexes turned to sum indexes
# and extra terms added to limit them to the relevant study period
# first, variable costs
sum {{z, t, s, o) in PROJ_DISPATCH, h in HOURS: period[h]=num($sensitivity_period)) hours_in_sample[h] * (DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * fuel_cost_hourly[fuel[t]] + DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * carbon_content[fuel[t]] * carbon_cost + DispatchGen[z, t, s, o, h] * variable_o_m[t]) + sum {{z, t, s, o, v, h) in PROJ_INTERMITTENT_VINTAGE_HOURS: period[h]=num($sensitivity_period)) hours_in_sample[h] * ((1-forced_outage_rate[t]) * cap_factor[z, t, s, o, h] * InstallGen[z, t, s, o, v]) * variable_o_m[t] + sum {{z, e, p) in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=num($sensitivity_period)) hours_in_sample[h] * (OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e] * ep_heat_rate[z, e]/1000 * fuel_cost_hourly[ep_fuel[z, e]] + OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e] * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] * carbon_cost + OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) * ep_size_mw[z, e] * ep_variable_o_m[z, e]) + sum {{z, e, h) in EP_DISPATCH_HOURS, p in PERIODS: p=period[h] and p=num($sensitivity_period)) hours_in_sample[h] * (DispatchEP[z, e, h] * ep_heat_rate[z, e]/1000 * fuel_cost_hourly[ep_fuel[z, e]] + DispatchEP[z, e, h] * ep_variable_o_m[z, e])
```

then, fixed costs for plants

```
+ sum {{z, t, s, o) in PROJECT_VINTAGES: v <= num($sensitivity_period) < project_end_year[t, v)}
sensitivity_add_row_to_output_file.run

InstallGen[z, t, s, o, v]
* (capital_cost_annual_payment[z,t,s,o,v] + fixed_cost_proj[t,v]) * 1000
* (1-(1/(1+discount_rate)^(years_per_period)))^discount_rate
+ sum {{z, e, p} in EP_PERIODS: p=num($sensitivity_period)}
  OperateEPDuringYear[z, e, p] * ep_size_mw[z, e] * ep_fixed_cost[z, e, p] * (1+discount_rate)^(p-base_year)
+ ep_size_mw[z, e] * ep_capital_cost_annual_payment[z, e] * 1000 * (1-
  (1/(1+discount_rate)^(years_per_period)))^discount_rate
+ sum {{z, s} in PROJ_HYDRO, p in PERIODS: p=num($sensitivity_period)}
  max {d in DATES, h in HOURS: date[h] = d and period[h] = p} max_hydro_flow[z, s, d]
  * hydro_annual_payment_per_mw * (1-(1/(1+discount_rate)^(years_per_period)))^discount_rate
# then, fixed costs for transmission and local T&D
+ sum {{z1, z2} in TRANS_LINES, p in PERIODS: p=num($sensitivity_period)}
  ((existing_transmission_from[z1, z2]+existing_transmission_to[z1, z2])/2)
  * transmission_annual_payment[z1, z2, first(PERIODS)] * (1-
  (1/(1+discount_rate)^(years_per_period)))^discount_rate
+ sum {{z1, z2} in TRANS_LINES, p in PERIODS: p=num($sensitivity_period)}
  (sum {v in VINTAGE_YEARS: v <= p < transmission_end_year[v]} InstallTrans[z1, z2, v] * transmission_annual_payment[z1, z2, v])
  * (1-(1/(1+discount_rate)^(years_per_period)))^discount_rate
+ sum {p in PERIODS, z in LOAD_ZONES: p=num($sensitivity_period)}
  (system_load_fixed[z, h] * ClearAnnualDemand[z, period[h]]/max(annual_demand_quantity_base_mwh[z, period[h]], 1e-6)
  + DispatchSystemLoad[z, h]
  - (sum {{z1, z} in TRANS_LINES} (transmission_efficiency[z, z2] * DispatchTransTo[z1, z2, h] - DispatchTransFrom[z, z2, h]))
  + (sum {{z1, z} in TRANS_LINES} (DispatchTransTo[z1, z, h] - transmission_efficiency[z1, z] * DispatchTransFrom[z1, z, h]))
  )

# total power generated (excluding transmission losses), same as above, assumed equal to load+surplus
sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * (system_load_fixed[z, h] * ClearAnnualDemand[z, period[h]]/max(annual_demand_quantity_base_mwh[z, period[h]], 1e-6)
  + DispatchSystemLoad[z, h]
  - (sum {{z1, z} in TRANS_LINES} (transmission_efficiency[z, z2] * DispatchTransTo[z1, z2, h] -DispatchTransFrom[z, z2, h]))
  + (sum {{z1, z} in TRANS_LINES} (DispatchTransTo[z1, z, h] - transmission_efficiency[z1, z] * DispatchTransFrom[z1, z, h]))
  )

# total load satisfied, including transmission losses, from Satisfy_Load constraint
sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * (system_load_fixed[z, h] * ClearAnnualDemand[z, period[h]]/max(annual_demand_quantity_base_mwh[z, period[h]], 1e-6)
  + DispatchSystemLoad[z, h]
  - (sum {{z1, z} in TRANS_LINES} (transmission_efficiency[z, z2] * DispatchTransTo[z1, z2, h] - DispatchTransFrom[z, z2, h]))
  + (sum {{z1, z} in TRANS_LINES} (DispatchTransTo[z1, z, h] - transmission_efficiency[z1, z] * DispatchTransFrom[z1, z, h]))
  )

# total cost of carbon (stripped-down version of total cost calculation)
sum {{z, t, s, o} in PROJ_DISPATCH, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * (DispatchGen[z, t, s, o, h] * heat_rate[t]/1000 * carbon_content[fuel[t]] * carbon_cost)
+ sum {{z, e, p} in EP_BASELOAD_PERIODS, h in HOURS: period[h]=p and p=num($sensitivity_period)}
  hours_in_sample[h] * (DispatchEP[z, e, h] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e])
  * ep_size_mw[z, e] * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] * carbon_cost)
+ sum {{z, e, h} in EP_DISPATCH_HOURS, p in PERIODS: p=period[h] and p=num($sensitivity_period)}
  hours_in_sample[h] * (DispatchEP[z, e, h] * ep_heat_rate[z, e]/1000 * carbon_content[ep_fuel[z, e]] * carbon_cost)
sensitivity_add_row_to_output_file.run

# generation from various sources, taken from Satisfy_Load constraint

# new wind projects

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * 
  sum {t, s, o, v in PROJ_INTERMITTENT_VINTAGE_HOURS: t=tech_wind} 
  (1-forced_outage_rate[t] * cap_factor[z, t, s, o] * InstallGen[z, t, s, o, v]),

# new troughs

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * 
  sum {t, s, o, v, h in PROJ_INTERMITTENT_VINTAGE_HOURS: t=tech_trough} 
  (1-forced_outage_rate[t] * cap_factor[z, t, s, o] * InstallGen[z, t, s, o, v]),

# new pv

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * 
  sum {t, s, o, v, h in PROJ_INTERMITTENT_VINTAGE_HOURS: t=tech_pv} 
  (1-forced_outage_rate[t] * cap_factor[z, t, s, o] * InstallGen[z, t, s, o, v]),

# geothermal

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * ( 
  sum {t, s, o in PROJ_DISPATCH: fuel[t]="Geothermal"} DispatchGen[z, t, s, o, h] 
  + sum {t, s, o in PROJ_DISPATCH: fuel[t]="Geothermal"} DispatchGen[z, t, s, o, h]) 
  * ep_size_mw[z, e] 
  + sum {z, e, h in EP_DISPATCH_HOURS: ep_fuel[z, e]="Geothermal"} 
  DispatchEP[z, e, h] 
  ),

# hydro (net of pumping and losses)

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * ( 
  1 - forced_outage_rate_hydro) * 
  sum {z, s in PROJ_PUMPED_HYDRO} DispatchPumpedHydro[z, s, h] 
  + sum {z, s in PROJ_PUMPED_HYDRO} StorePumpedHydro[z, s, h] 
  * (avg_hydro_dispatch_all_sites[z, date[h]] - min_hydro_dispatch_all_sites[z, date[h]]) * 24 
  ) ,

# Nuclear

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * ( 
  sum {t, s, o in PROJ_DISPATCH: fuel[t]="Nuclear"} DispatchGen[z, t, s, o, h] 
  + sum {z, e, p in EP_BASELOAD_PERIODS: p=period[h] and ep_fuel[z, e]="Nuclear"} 
  StorePumpedHydro[z, s, h]) 
  * ep_size_mw[z, e] 
  + sum {z, e, h in EP_DISPATCH_HOURS: ep_fuel[z, e]="Nuclear"} 
  DispatchEP[z, e, h] 
  ),

# Gas

sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * ( 
  sum {t, s, o in PROJ_DISPATCH: fuel[t]="Gas"} DispatchGen[z, t, s, o, h] 
  + sum {t, s, o in PROJ_DISPATCH: fuel[t]="Gas"} DispatchGen[z, t, s, o, h]) 
  * ep_size_mw[z, e] 
  + sum {z, e, h in EP_DISPATCH_HOURS: ep_fuel[z, e]="Gas"}
DispatchEP[z, e, h]
},

# Coal
sum {z in LOAD_ZONES, h in HOURS: period[h]=num($sensitivity_period)} hours_in_sample[h] * (  
  sum {{z, t, s, o} in PROJ_DISPATCH: fuel[t]="Coal"} DispatchGen[z, t, s, o, h]  
  + sum {{z, e, p} in EP_BASELOAD_PERIODS: p=period[h] and ep_fuel[z, e]="Coal"}  
    (OperateEPDuringYear[z, e, p] * (1-ep_forced_outage_rate[z, e]) * (1-ep_scheduled_outage_rate[z, e]) *  
     ep_size_mw[z, e])  
  + sum {{z, e, p} in EP_DISPATCH_HOURS: ep_fuel[z, e]="Coal"}  
    DispatchEP[z, e, h]  
)  
>> ($sensitivity_outfile);

---

sensitivity_add_base_case_to_output_file.run

# copy the base case results into the current sensitivity output file.  
# also relabel the rows to match the current sensitivity case.
shell ('tail -n +2 ' & $sensitivity_basefile  
& ' | sed "s/^"base case","",/"' & $sensitivity_name & '","' & gsub($sensitivity_value, "[ ^A-Za-z0-9 ]", "\&") & "",/"'  
& ' >> ' & $sensitivity_outfile);

---

sensitivity_close_output_file.run

close ($sensitivity_outfile);