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Impact of Large-Scale Energy Storage on the Least-Cost State of Power Systems

Case Study California

Master's Thesis in Sustainable Energy Systems

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Department of Energy and Environment
Division of Physical Resource Theory
Chalmers University of Technology
Gothenburg, Sweden 2015

Thesis for the Degree of Master of Science
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Abstract

Energy storage is expected soon to become an increasingly important part of electricity systems around the world. This is driven by direct technology-specific policies, the expansion of variable electricity sources based on solar and wind power, and the decreasing capital cost of storage solutions. This report addresses the impact of a large-scale employment of this technology class on the composition and operation of a power system. It thus explores the shifts in value of the generators and their output once the possibility of transferring significant amounts of electric energy between different hours is provided.

For this purpose, a stylized version of the power system in California is analyzed and described by a deterministic linear model. The investment in the system is optimized together with the dispatch over one year. To assess the impact of increasing levels of storage power capacity under different carbon cost scenarios, these parameters are varied exogenously. This approach is complemented by two simpler models, which serve to illustrate some more intricate aspects of the system's behavior.

The direct arbitrage mechanism introduced by the operation of the storage causes the value of the generators with the cheapest cost to be higher and consistently leads to the expansion of wind power as well as the increase of electricity production from base load (biomass) power plants. Under some emission cost scenarios the storage-induced rise of wind power capacity results in the reduction of the economic value of base-load power plants and the net increase of the output of gas-fueled peaker plants. The relative competitiveness of wind and solar power is equally affected by an increase of the storage power capacity, which causes the expansion of one of them at the expense of the other in scenarios with high storage capacities. Both the levelized cost and the demand-correlation of the electricity from these variable sources have been found to play a pivotal role in the final outcome.

Keywords: linear optimization, energy storage, electricity generation, variability, arbitrage, wind power, photovoltaics.

Contents

1	Introduction	1
2	Background	3
2.1	Why California?	4
2.2	Previous Studies	7
3	Modeling Approach	11
3.1	The Model A ³¹²⁵	11
3.1.1	Temporal Structure and Investment Decisions	12
3.1.2	Main Constraints and Implementation of Policies	13
3.1.3	Generator Operation and Capacity Availability	14
3.1.4	Storage Operation	15
3.1.5	Hourly Input Data	15
3.2	The Model B ²	16
3.3	The Model B ³	18
4	Base Scenario Parameters	21
4.1	Capacity Availability and Generator Operation	21
4.2	Hourly Input Data	22
4.3	Properties of Technologies	22
4.3.1	Dispatchable Generators	22
4.3.2	Variable Electricity Sources	23
4.3.3	Storage Technologies	24
4.3.4	Other Exogenous Parameters	24
4.4	Scenarios	25
5	Results and Discussion	27
5.1	Least-Cost State of the Base Scenario	27
5.2	Varying Storage Capacity and Cost of CO ₂ Emission Allowances	33
5.3	OBSERVATION A: Choice of Storage Technology	36
5.4	OBSERVATION B: Increasing Generation from Biomass Plants at Low Carbon Cost	39
5.5	OBSERVATION C: Increasing Wind Capacity with Increasing Storage Capacity	41
5.6	OBSERVATION D: Replacement of Biomass Power Plant Output with Electricity from NGCC Plants	44
5.7	OBSERVATION E: Impact on Photovoltaics	48
5.8	Limitations	53

6 Conclusion	57
6.1 Future Work	59
Appendices	61
A Technical and Economic Properties of Storage Technologies	I
A.1 Properties of electrochemical storage types	I
A.2 Properties of non-electrochemical storage types	IV
B Technical Model Documentation	VII
Bibliography	XVI

Chapter 1

Introduction

While nations and other entities strive to mitigate the environmental impacts of their energy supplies [1], the changing relative economic performances of different electric power sources provide increasingly large economic momenta for shifts in the composition of the world's power systems. At the same time the technical realities in the new states of those systems call for novel solutions and paradigmatic shifts. The production of electricity typically accounts for a major share of energy related GHG emissions (13.9 % in California [2]). In addition to this, the need for structural changes is all the more pressing as several future and ongoing transitions pose new challenges related to the operation and expansion of these power systems. This includes the need for high quality power services as the demand gets more sophisticated, the necessity to replace large chunks of aging capacity, the increasing emphasis on distributed generation, and the rising demand from previously non-electrified services, such as transportation [3–5].

In this context, one of the most prominent ongoing changes is the rapid expansion of renewable capacity, which on a global scale surpassed the installation of fossil-fuel based generators in 2013 [6]. Especially solar and wind power are expected to play an increasingly large role in future power systems.

The inherent intermittency and variability of these sources call for the overturn of the incumbent mindset which considers a static load to be served by a flexible power system. On the other hand it is often overlooked that wind and solar power sources share a large part of their variability with the system's load patterns and a large part of their intermittency with conventional fossil-fuel powered generators (due to forced outages) [4, p193]. This leads to the conclusion that in principle the current systems are not as unprepared for the challenges to come as it seems at first sight, but that an intensification of mitigating actions and the adoption of novel solutions is required as wind and solar power commence to make predominant contributions to the electricity supply.

A broad range of such technical, organizational, and strategic measures are known and partly about to be scaled to significant volumes; they range from the large-volume use of energy storage and demand-side management to improvements on the system's level, including grid expansion and the geographic diversification of the variable generator fleet. Since most of these approaches are gaining importance in many power systems around the world, the future is likely to see a combination of many of these strategies. In this

study an emphasis is put on the mass-scale employment of storage solutions primarily for following reasons:

- Storage technologies are especially versatile and can be used for the provision of a wide range of services in power systems, the demand for most of which increases as the amount of electricity produced from variable sources rises.
- The high flexibility on a broad range of time scales makes this class of technologies especially disruptive when compared to other strategies.
- The upscaling of the production and the decrease of capital costs is expected to cause a surge of the use of batteries for novel applications in the near future.
- Recently implemented demand pull policies in some parts of the world aim specifically at the promotion of storage solutions (see section 2.1).

Many studies have been conducted to assess the role of grid-connected electricity-to-electricity energy storage as a support to the future development of electric power systems. Similarly, the economic performance of storage solutions as investment projects have been repeatedly at the center of academic interest. In contrast, a much less considered aspect consists in the impact of storage solutions on the development of the rest of the system if introduced on a large enough scale. It is intuitively clear that the possibility of storing large volumes of energy to discharge it during later hours adds a whole new dimension of flexibility to the system, causing shifts in the relative economic performance of the other assets and ultimately affecting the system with respect to both its operation and expansion.

The project presented in this report seeks to identify the possible shifts of this kind within a highly stylized power system based on the one of the U.S. state California. This positive study is exploratory in nature and by design limited to the generator fleet of the chosen reference system. The central questions to be answered within the boundaries of the model can be stated as:

- *Which drivers of shifts in the value and employment of different generator technologies can be identified for varying storage capacity?*
- *What magnitudes of these effects can be expected?*
- *Which are the underlying mechanisms of these shifts?*

A cost-minimizing model was developed for this purpose, which simultaneously determines the optimal modifications to the initial generator and storage capacities, and which assesses the least-cost operation of these asset classes to cover a given demand during one year. Using a real system as a loose reference is helpful in determining the potential magnitudes of the impacts to be studied. However, while this study is based on a highly stylized model of the Californian power system, it is important to bear in mind that its intended use is neither a quantitative positive statement about this system's future development, nor the conceptualization of an optimized future system state. Furthermore, even though the use of different storage technologies is analyzed, the determination of the optimal use of various storage types under different conditions is beyond the scope of this project.

Chapter 2

Background

Storage solutions can be used to transfer energy from hours/days/seasons of low effective load¹ to periods of high load. This is especially useful in systems where the penetration of variable renewable power sources has reached such high levels that the variability of these power sources poses a challenge in matching demand and supply of electricity. While mainly pumped hydro storage is used on a significant grid-level scale as of today [7], many other storage technologies are known for various applications. Some of these technologies are expected to reach market maturity in the coming years [8], allowing them to be employed in volumes large enough to make substantial contributions to the functioning of the power system.

This study focuses on storage solutions due to their expected high potential, decreases in the capital costs of different technologies, and policies fostering their wide-spread application. The value of storage in the power system arises from a large variety of services, which are partly overlapping and partly more or less specific to certain subsets of storage types [9]:

- Long-term arbitrage on a time scale between 1 hour and several months makes use of storage to even out differences in marginal costs due to temporal differences in demand and/or supply. This application calls for large volumes of both energy and power capacity, and high energy-to-power ratios, thus favoring technologies such as compressed air or pumped hydro energy storage.
- The provision of what is commonly known as ancillary services includes frequency and voltage regulation, load following, as well as spinning and non-spinning reserve. It is characterized by short time-frames and high-frequency charging cycles. Flywheels and various batteries show a high potential for this application.
- Demand shifting and peak reduction is also driven by differences in marginal electricity prices on a diurnal basis. In the long term this has the additional system benefit of avoiding the investment in additional generating capacity to cover the peak load.

¹*Effective load* is defined as the total demand minus the net output from wind and solar generators throughout the remainder of this report.

- When used at strategical nodes of the electricity grid, storage serves to reduce the peak power to be transmitted on capacity-constrained connections. This helps to relieve congestion in the grid and to defer or avoid the expansion of the grid infrastructure.

The technical and economic differences of these applications lie mostly in the duration of the charging and discharging cycles and the value of the storage energy and power capacities. The total value of the storage assets in the system arises from the simultaneous use for several applications, known as benefits-stacking [9]. The study described in this report covers the use of storage for arbitrage on time-scales of one hour and beyond, as well as the deferral of investments in generating technology.

The largest storage facilities in California as of today are either closed-loop or open-loop pumped-hydro plants, complemented by small amounts of lithium-ion, lithium iron phosphate and sodium-sulfur batteries, as well as thermal storage. The total power capacity of these additional (non-hydro) technologies is of the order of 60 MW. Much larger volumes of almost 800 MW are currently being announced, contracted or constructed (not taking hydropower into account), including 300 MW of in-ground compressed air storage [7].

2.1 Why California?

Within the United States California acts as a role model in the application of clean power sources and novel technological solutions. Thanks to its ambitious policies the electricity generation from solar power more than doubled from 2013 to 2014 and provided some 5 % of the total generation in 2014. As a result, the rapid expansion of non-fossil electricity generation more than compensated for the drought-induced decline of generation from hydro power observed in 2014 [10]. Specifically for the United States, a large variety of studies reaches the conclusion that a power system generating the vast majority of its electric energy from renewables, specifically wind and solar, is a realistic and cost-effective goal [4, 11, 12] using currently available technology.

This study is based on a highly stylized model of the power system in California. While several geographic entities around the world would be good candidates to serve as a reference for a study like this, California is particularly interesting for a number of reasons:

- The relatively high employment of renewable energy sources (by U.S. standards), together with the emission targets, makes scenarios with a high penetration of wind and solar power credible.
- This is supported by the state's favorable solar and wind resource endowment.
- California has seen some drastic policies over the last years, e.g. leading to the retirement of many power plants with once-through cooling and the second-last nuclear power plant. Together with the expected continuation of the rising penetration of wind and solar power this turnover of capacity causes new challenges, which led some to call this state "a leading case study on the need for new methods to evaluate

and procure flexible capacity” [13].

- Recent policies aiming at the promotion of storage technologies (see section 2.1) and the studies discussed below suggest that large-scale storage might indeed play a significant role in the near-term development of this system. To some extent this is even independent of the capital cost development of the storage technologies.
- The high degree of transparency in the activities of the relevant authorities and the large academic interest in the Californian power system lead to an excellent availability of data which facilitates the development of the model used in this study.

It has been estimated that the cumulative effect of the policies currently implemented in California might indeed suffice to reach the goals on the way to an 80 % emission reduction until 2050 [14], the ultimate target expressed in a governor’s executive order from 2005 [15].

The policies described below are both relevant input parameters to the model and give a glimpse at the transformations currently underway in the Californian power system.

The Public Utilities Commission’s Energy Storage Decision

The energy storage mandate is a technology pull policy aiming at the creation of a market for “commercially available [...] technologies [...] that may have been demonstrated but are not yet generally deployed on the grid in California.” [16] The Public Utilities Commission motivates this decision by the necessity to maximize the value of the state’s generation and transmission investments. In particular, the purpose is to obtain contributions to the operation of the grid, including peak reduction, the increase in reliability/provision of ancillary services, and the reduction of the need for investments in transmission and distribution capacity [16, p6]. While the potential value of additional storage has thus been identified, several barriers obstruct its wide-spread employment. These barriers center around the lack of markets, regulatory frameworks, experience, price signals and methods for the assessment of cost-effectiveness [16, p3]. In this context the authorities draw an analogy to the situation of rooftop solar PV prior to the commencement of the successful California Solar Initiative in 2007 [16].

The procurement targets in terms of additional power capacity are spread among the three large investor owned utilities and amount to a total of 1,325 MW [16, p8]. These assets are to be operating and connected to the grid “no later than the end of 2024” [17, p2]. A differentiation is made concerning the grid level the storage ought to be connected to, with predefined capacities allocated to the transmission, distribution, and customer level [18]. No constraints are put on the choice of the technologies, with the exception of the exclusion of pumped storage projects with a capacity higher than 50 MW [17, p5].

California Renewables Portfolio Standard (RPS)

The California Renewables Portfolio Standard was established in 2002 by the California Public Utilities Commission and the California Energy Commission and has been modified

several times until 2011 [19]. In its final form it requires all retail sellers to procure 33 % of energy from eligible renewable sources as of 2020 and each of the years thereafter [20]. As of 2014 this figure has reached 20.9 % [21]. For the time after 2020 increasing targets are being proposed. However, a final decision is likely to be postponed until the current scheme's effectiveness could be evaluated [22].

Eligible facilities are required to use renewable resources or fuels such as geothermal energy, or derived fuels in any state of matter, municipal waste, all forms of ocean energy, and solar and wind power. Small hydropower plants installed after 2006 are considered eligible if their capacity is below 30 MW. However, the details of the regulations are rather intricate and the decisions highly site-specific as the authorities aim at a minimization of the facilities' impact on the other services derived from the hydraulic and aquatic systems [23]. This also justifies the exclusion of larger plants where the eligibility is limited to incremental generation obtained from efficiency improvements [24]. Electricity stemming from the discharge of a storage devices can contribute to the RPS scheme if the storage is directly connected to an eligible source [24].

Emissions Trading

With the California Global Warming Solutions Act of 2006 the legislators expressed their intent to slash the state's greenhouse gas emissions to reach the 1990 levels by 2020. A "market-based compliance mechanism" was suggested for this purpose [25, p1]. Consequently, the California Air Resources Board established the cap-and-trade regulation; by covering all large emitters it is expected to amount to 85 % of the state's total emissions starting from 2015 [26, p4]. The yearly cap is set to decline until the end of the scheme [26, p4]. A price floor has been defined as the minimum price per allowance, and is set to 10 \$ per ton of CO₂ equivalent in 2012, increasing by 5 % per year plus the rate of inflation [26, p5]. To avoid price spikes, a certain amount of allowances is set aside during each period, to be offered at pre-determined yearly increasing prices between 40 \$ and 50 \$ [26, p5]. So far allowances have been traded at a price not much higher than the floor [26, p9ff.]. The power sector is projected to contribute to the scheme with 20 % in 2020 [26, p4].

Other Relevant Policies

The three policies above are directly implemented in the model. Several other policies have directly or indirectly shaped the power system in a profound way. Their influence on the model used in this study lies in either their impact on the state's current generator fleet or the support for intricate system developments, which contribute to the limitation of the model's applicability.

- **Emissions Performance Standard:** The Senate Bill 1368 from 2006 defines a performance standard of 0.5 t/MWh of CO₂ for all base-load-serving power plants [27]. Since this value corresponds to the emission factor of a modern NGCC plant, the standard effectively excludes the option of adding new coal power to the system, or extending any existing contracts with these plants [28]. This decision justifies the

exclusion of additional coal power in model.

- **The Once-Through-Cooling Water Policy** was established by the State Water Resources Control Board to “reduce the harmful effects associated with cooling water intake structures on marine and estuarine life” [29]. It requires existing power plants to be upgraded to the best technology available, or to be adapted in a way to achieve a comparable impact mitigation. This policy was considered a main challenge in terms of maintaining the flexibility of the electricity system [30]. However, as those power plants for which an upgrade was found to be not profitable retired prior to or in 2014 [31, p4], it is not explicitly included in the model.
- **The California Solar Initiative (CSI):** Through the CSI the state of California was aiming at the installation of 1,940 MW of solar generation capacity between 2007 and 2016 [32]. The incentive was provided by a fixed cash contribution per unit of power capacity. This subsidy was reduced in several steps depending on the total volume of capacity installed within the framework of the program.
- **Self-Generation Incentive Program (SGIP):** Together with the CSI the SGIP is the second component of the CPUC Distributed Generation Programs. Its purpose is to cut peak-loads by providing incentives for the installation of electricity generators on the customer’s side of the utility meter. The incentives are provided in the form of subsidies per unit of installed capacity. While also non-renewable CHP projects are qualified to participate in the scheme, the subsidies are lower than for emission-free technologies. An emphasis is put on the support of emerging technologies such as storage and fuel cells [33]. This policy (together with the CSI) illustrates that the differentiation of various grid levels is a relevant expansion to the model presented here. This is discussed further in chapter 6.

2.2 Previous Studies

A number of studies have been conducted to assess the optimal strategies to foster the expansion of renewable power sources in the most general sense of the term, and to deal with the variability of the electricity production from wind and solar power. In addition, some analyses focus on the contribution of storage to cover the demand for various services [13]. However, storage capacity is generally not considered a free parameter, but either optimized to achieve cost-minimization (if a model includes the turnover of capacity), provided exogenously to the model under rather conservative assumptions (if the model focuses on the optimization of the system operation), or considered to have low enough capacity not to affect the marginal cost of electricity (if the focus is the storage’s operation alone).

The widely quoted study *Investigating a Higher Renewables Portfolio Standard in California* by E3 [34] analyzes the potential and implications of a 50 % renewable energy portfolio in California by 2030. It employs a model combining mathematical programming with a Monte-Carlo analysis [35] and focuses on system flexibility and the operational challenges resulting from a higher penetration of variable renewables. Thereby, various scenarios comprising different compositions of static generator fleets are considered and fed into the model as exogenous parameters.

The main challenge identified by this study is the over-generation from non-dispatchable sources, especially solar power, requiring excessive levels of curtailment during many hours of the day [34, p15]. The investigated mitigating modifications to the system include “advanced regional coordination”, demand response, energy storage and resource diversification. The authors conclude that none of these measures lead to a full relief of the problem but find that their effects are additive. While they express their skepticism about the future role of storage in the light of environmental concerns (pumped hydro) and low economic performance (all others) [36], their findings together with the very recent developments in cost reduction and employment of batteries [8, 37] suggest that large-scale grid-connected energy storage could indeed play a central role in the efficient operation of future power systems.

Based on mathematical programming, the *California 2030 Low Carbon Grid Study* (LCGS) is being conducted by a consortium around the US National Renewable Energy Laboratory and explores the implications of a 50 % decrease of the power sector emissions by 2030 with respect to the level in 2012 [38]. It analyzes the operation of an exogenously devised generator fleet. Compared to the study by E3, the LCGS puts an emphasis on a high portfolio diversity and encompasses a topologically more complete approach, including both intra-state congestion and the dispatch of the whole Western Electricity Coordinating Council² (WECC) area’s system [38]. The main conclusion of this study is the feasibility of a net rate reduction in 2030 compared to 2012, while meeting a 50 % emissions target, which has been identified as an important intermediate step toward the 80 % reduction envisioned for 2050 [39].

In the primary scenario of this study the amount of storage in the system is set to the current CPUC mandate target plus an additional 2,200 MW. Its role in the system’s hourly dispatch consists mainly in the shift of energy from the nightly hours of low demand to the evening peak not covered by solar power output [38]. The primary role of storage in the system has been found to consist in the provision of regulation and contingency reserves [38], where it largely replaces the historic contribution from gas and hydro plants [40, figure 6.4].

Compared to these two models, the *SWITCH model* optimizes both the operation of and the investment in the expansion of power systems and therefore bears significant resemblance to the model presented here. Offering a high-resolution representation of the U.S. Western Electricity Coordinating Council area it comprises 14 U.S. states as well as parts of Canada and Mexico. This high geographic resolution goes at the expense of the temporal dimension. Investments are made during 4 distinct periods between 2015 and 2055.

In a 2013 study by Milena *et al.* this model was used to explore the consequences of drastically decreasing costs for solar power (1 \$/W for central PV from 2020 on), which is envisioned within the framework of the U.S. Sunshot Initiative [41]. The authors conclude that under these conditions solar power could provide a third of the electricity in the WECC by 2050, while large amounts of storage (29 GW of compressed air energy storage and 3 GW of batteries) are a viable part of the cost-minimized system state.

Complementary to these works on the entire system several studies consider storage as an investment asset, and analyze its economic performance within an exogenous power system [13, 42].

Byrne *et al.* [42] find the revenue from the participation in ancillary markets to be four times

²comprising the eastern states of the U.S., as well as parts of eastern Canada and Mexico

higher than from pure arbitrage. Thereby, a large fraction of 95 % of the maximum revenue (which would require perfect market foresight) could be achieved using a simplistic trading strategy. This importance of ancillary markets is confirmed by Cutter *et al.*; in addition, they conclude that storage solutions are highly competitive with respect to combustion turbines in these markets, which is attributed to their superior flexibility.

Chapter 3

Modeling Approach

The main analysis presented in chapter 5 is based on the Model A³¹²⁵, which features a high temporal but low topological resolution. The primary objective of this model is to assess the changes of the operation and composition of the system in its least cost state upon the introduction of large volumes of storage capacity. The complex shape of the multiple time series describing the electricity demand and the output of the variable generators cause the behavior of the individual technologies to be strongly dependent on the season of the year. To isolate relevant mechanisms while avoiding these complexities, two complementary models B² and B³ were devised.

3.1 The Model A³¹²⁵

The Model A³¹²⁵ combines the dispatch and the expansion of a stylized single-node power system in order to assess its least cost composition and operation. It is implemented as a linear program. The model time frame covers a whole year approximated by 3125 time slices of variable duration, each of which comprises 2.8 hours on the average.

The set of available technologies is based on the state of the power system in California as of 2014. In total, seven different dispatchable generator technologies are used, complemented by six variable electricity sources whose temporal output pattern (hourly capacity factor) is defined by an exogenous time series. From the seven storage technologies included in the model, only three are finally relevant. No distinction between individual power plants or other assets is made: The technologies are represented by a single set of decision variables.

Figure 3.1 provides an overview of the components included in the model. The most important structural aspects are discussed in this chapter. The relevant input parameters describing the costs and operation of the system are presented in chapter 4.

STRUCTURE	GENERATORS	VARIABLES	POLICIES
1 Year	Geothermal	Photovoltaics	RPS
3125 Slots/Year	Hydro	Wind 1-4	Storage Capacity
	Biomass	CSP	CONSTRAINTS
HOURLY DATA	Coal	STORAGE	Demand
Load	Nuclear	Pumped Hydro	Reserve Margin
Photovoltaics CF	NGCC	NaS Batteries	Policies
Wind 1-4 CF	Gas Turbines	Compressed AES	Wind/Solar CF
CSP CF			
	COSTS	Fuel Cost	DECISION VAR.
	Capital Cost	Variable O&M	Power per Slot
	Fixed O&M	Carbon Cost	Capacity
OBJECTIVE			
Total Cost			

Figure 3.1

Key elements of the Model A³¹²⁵. The investment in/operation of the assets are optimized simultaneously.

3.1.1 Temporal Structure and Investment Decisions

A single representative year is optimized and analyzed. While this introduces large distortions due to the implicit assumption of constant fuel prices, unlimited lifetimes of initial capacities, and a fixed system composition, it allows for a more complete interpretation of the mechanisms at play and is thus justified by the qualitative and exploratory nature of this study. The year 2020 is chosen as a reference; this choice is motivated by the target year of the main relevant policies in California. The costs and operational parameters were primarily gathered for the year 2014. Where applicable they are projected to 2020 using the corresponding escalation rates.

The capacities of the various assets are treated as positive variables in the model. The volumes available for the production or storage of electric energy are composed of

- the **initial capacities** based on the composition of the generator fleet in California in the year 2014, reduced by the capacity of those generators which are expected to reach the end of their lifetimes until the reference year 2020; and
- any **capacity additions** which are a viable component of the least-cost state of the power system and therefore of the solution found by the cost-minimizing algorithm.
- In addition, parts of the initial capacities deemed available in 2020 are **retired** if their value is not high enough to justify the fixed costs associated with their presence in the system.

Since the model covers a single year only, investment costs are expressed as equivalent annuities. These are calculated by using standard technology-specific capital recovery factors. Modifications to the power plant fleet are subject to various technology-specific constraints, reflecting the limited potential of certain technologies, either due to resource

constraints (geothermal power, hydropower) or political decisions (hydropower (again), and nuclear power).

3.1.2 Main Constraints and Implementation of Policies

The demand in the system is assumed to be inflexible and is modeled as an equality constraint. At the same time, curtailment of variable power generation is made possible by using the maximum power output of these technologies as an upper bound to their respective electricity production.

The required planning reserve margin is 15 % higher than the maximum power demand throughout the year and must be covered by the sum of the power capacities of the dispatchable generators and the installed storage.

In addition, the three policies described in section 2.1 are explicitly modeled:

- The storage procurement target is assumed to be effective in 2020, the base year of the scenarios considered here. It is expressed as

$$\sum_s P_s = P_{s,\text{target}} \quad \text{with} \quad s \neq \text{pumped hydro storage} \quad (3.1)$$

with the target value $P_{s,\text{target}}$ set exogenously as a free parameter. P_s are the power capacities of all storage technologies s .

- The Renewable Portfolio Standard is implemented as a lower bound on the total electricity production from a certain set of generators, which is comprised of solar, wind, geothermal, and biomass power plants:

$$\frac{\sum_{t,r_{\text{RPS}}} d_t p_{r_{\text{RPS}},t}}{\sum_{t,r} d_t p_{r,t}} \geq \xi_{\text{rps}} \quad (3.2)$$

where $r \in \{i, g\}$; r_{RPS} denotes the technologies eligible to contribute to the RPS, and ξ_{rps} the RPS target, set to 0.33. d_t is the length of the time slot t . $p_{r,t}$ is the power output of technology r during the time slot t .

As the difference between large and small hydro power is not explicitly included in the model, the contribution of this generator type to the fulfillment of the RPS is omitted. This is also justified by the relatively small incremental potential of hydropower [43].

Since the model approximates the RPS requirement by a constraint on the energy *produced* by renewable sources (instead of the energy provided to the load) the complication related to the eligibility of discharged electricity is avoided at the expense of including a spurious contribution from the electricity lost due to the limited round-trip efficiencies.

- Since the contributions from the power sector to the total greenhouse gas emissions are limited, the cost for the emission allowances is expressed as a fixed price p_{carb} in

dollars per weight unit of carbon dioxide. It is implemented as an addition to the fuel cost for the emitting power plants $g \in \{\text{coal, ngcc, natural gas}\}$

$$c_{vc,carb,g} = p_{carb} \left[\frac{\$}{t_{CO_2}} \right] \cdot i_g \left[\frac{t_{CO_2}}{MWh_{fuel}} \right] \quad (3.3)$$

with i_g the emission intensity of the fuel used by the generator g : $i_{coal} = 0.340 t_{CO_2}/MWh_{fuel}$ and $i_{natural\ gas} = i_{ngcc} = 0.202 t_{CO_2}/MWh_{fuel}$.

3.1.3 Generator Operation and Capacity Availability

During each time slot the output from all the generator technologies is limited by the installed capacity. In addition, the total electric energy available throughout the year is constrained by a maximum capacity factor for the base load power plants (geothermal, hydro and nuclear power; see table 4.1), or as an absolute total, to reflect the constrained availability of economically recoverable fuel (biomass).

Due to the exogenously defined monthly water inflow available for electricity generation by the hydropower plants, this technology requires particular attention. The total yearly energy from hydropower is limited to the installed capacity times a factor obtained from the actual aggregate output of the real-world plants. The effective energy inflow can either be stored for use during the next month or converted to electricity during any of the month's time slots. The energy available at the end of each month m is calculated as

- the energy in the impounding reservoirs left from the last season $m - 1$,
- plus the additional energy from the inflow,
- minus the total integrated power output during m .

The monthly inflows are expressed as fractions of the total yearly energy output. The amount of energy left at the end of the month is limited by the storage capacity of the reservoirs. In the model, this capacity is set to the maximum energy inflow among all months times a factor derived from real-world data. In addition, the energy output is spread over the year by the requirements that

- the level of total stored energy cannot decrease by more than 50 % from one month to the next, and
- for certain months the stored energy as a fraction of the maximum inflow during any month must be larger than a certain value (0.75 in June, to guarantee the use of hydro power during fall).

As will be shown further on, the aggregate effect of these constraints leads to a rather realistic monthly use of hydropower when compared to the real-world system.

3.1.4 Storage Operation

Storage is effectively used as a generator with constraints on the power output and the total energy available during each time slot. The charging level during the time slot t is calculated as the sum of

- the energy $e_{s,t-1}$ remaining from the slot $t - 1$, reduced by the leakage losses:

$$+e_{s,t-1} (1 - \eta_{s,\text{leak}})^{0.5(d_t + d_{t-1})};$$

- the charging power $p_{\text{ch},s,t}$ integrated over the duration of the time slot t , reduced by the round-trip efficiency: $+\eta_s p_{\text{ch},s,t} \cdot d_t$;
- the negative discharging energy $-p_{\text{dc},s,t} \cdot d_t$.

The total charged energy is limited by the installed storage energy capacity, which is again reduced by the limited depth of discharge. Some intricate properties of individual technologies are neglected. This especially includes the combustion of natural gas associated with the operation of the current compressed air energy storage facilities [44].

3.1.5 Hourly Input Data

A set of hourly time series serves to describe the demand pattern, as well as the cumulative output from the solar technologies and the wind turbines at various locations. In the case of the variable generators this data expresses the hourly capacity factor and thus the hourly power output if scaled by the corresponding capacity.

The optimization of a complete year is desirable to obtain a valid representation of the system—especially concerning the charging cycles of storage and the operation of the hydro power plants. However, given the computationally demanding optimization of the storage's operation it is important to obtain a good trade-off between completeness and computational feasibility. While many comparable models include a crude approximation of the total year as a small set of representative temporal slices, the approach chosen here is based upon the dynamic aggregation of a small number of neighboring hours into a respective time slot, taking into account the specific shape of all seven sets of hourly resolved input data (4× wind, 2× solar and demand). The following algorithm loops over all hourly time series and all hours, starting from the first:

1. A threshold is calculated as a certain fraction of the maximum spread of values within a certain range around the current hour
2. More hours are added to the current time slot until the maximum deviation of any of the slot's hours is larger than the threshold defined in 1.
3. If the deviation is too large, a new time slot is started.
4. Once all time series have been partitioned, the final time slots are found by calculating the common refinement.

The final number of slots is thus a function of the thresholds used in this algorithm: Smaller thresholds lead to smaller deviations between the hourly input data and the final approximation, yet increase the number of slots.

It is intuitively clear that the value of this approach decreases for higher numbers of time series, as the final temporal partition of the year has to capture more and more details of the original input data. It has been found that for the specific case considered here no real advantage is given compared to the use of slots with a fixed temporal length.

3.2 The Model B²

The two-hour Model B² serves to illustrate the basic mechanism of the expansion of wind power driven by the introduction of storage capacity. It is defined as follows:

- The temporal dimension is restricted to two representative hours with different

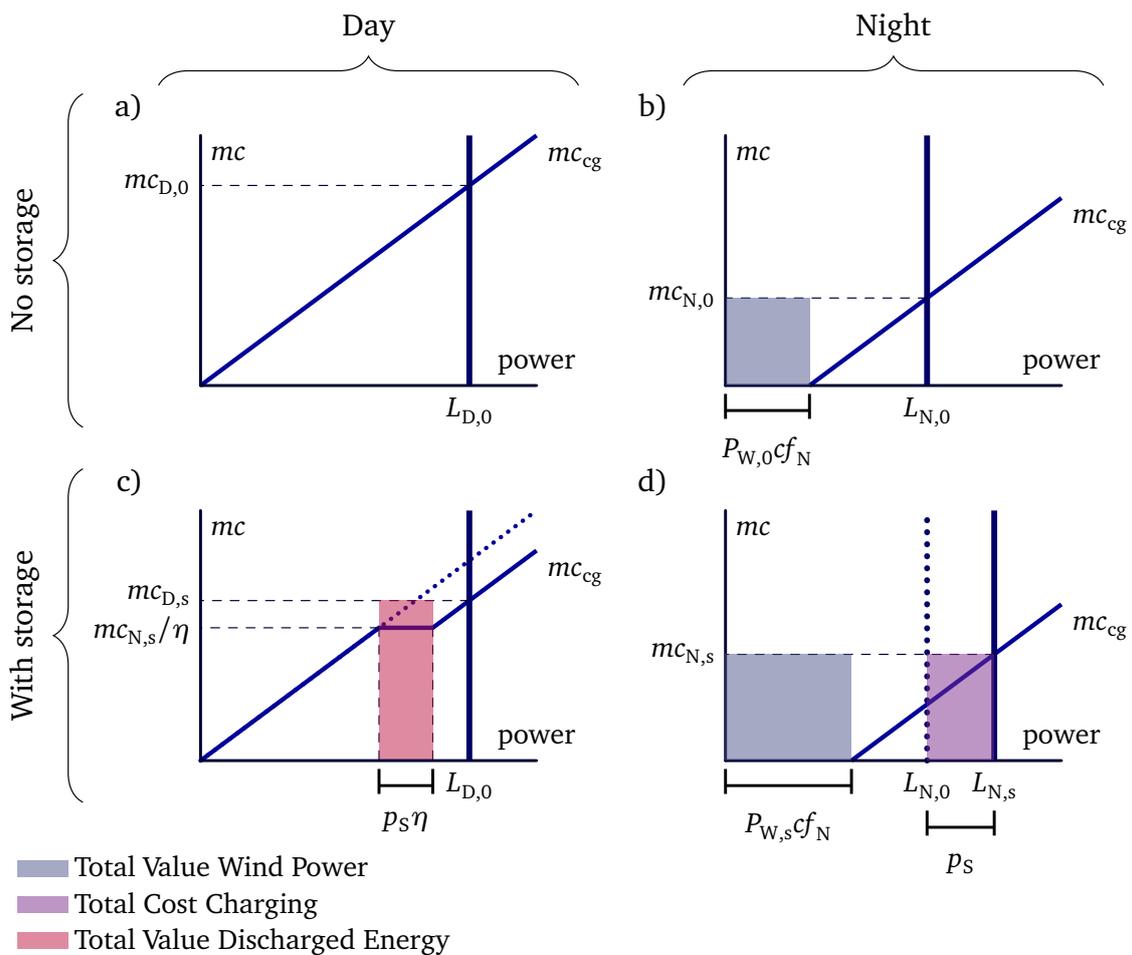


Figure 3.2

Sketch of the complementary minimalistic Model B²: The system is represented by two time slots per year (day and night).

electricity demand levels ($L_N = 25$ GW at night (right column), $L_D = 35$ GW during the day, left column).

- The variable cost of the conventional generators increases linearly with demand; a slope of $dm_{c_{cg}}/dp = 2.5$ \$/MWh/GW is chosen as a rough approximation. This slope is varied to approximate the impact of a higher cost on carbon emissions, which in the system considered here primarily causes the rise of the variable costs of those power plants which cover the peak load.
- Wind power is the only endogenous generator capacity (P_W). It comes at a specific equivalent annual cost of $c_W = 150,000$ \$/MW/yr and delivers output at night at a capacity factor $cf_N = 0.85$. The total capacity factor is thus $cf = 0.5cf_N = 0.425$.
- The storage power capacity P_S is set exogenously and poses an upper limit to the power charged during the night. The charging cycle occurs with an efficiency of $\eta = 0.6$.

A sketch of the model is shown in figure 3.2. The installation of wind power capacity is driven by the marginal electricity price during the night $mc_{N,0}$ (b). The transfer of energy from night to day increases the nightly demand by p_S , thereby raising the electricity price to $mc_{N,s}$. The discharge during the day (c) corresponds to an equivalent generator delivering p_S of power at an effective variable cost of $mc_{N,s}\eta^{-1}$. This lowers the daily price of electricity to $mc_{D,s}$ as long as the transfer of energy is viable, i.e. $mc_{D,s} \geq mc_{N,s}\eta^{-1}$. The addition of wind turbine capacity will be justified as long as the marginal value mv_W of the wind capacity is larger than its specific equivalent hourly cost. The equality of this condition allows for the calculation of the optimum amount of wind capacity in dependence on the available storage power capacity:

Case A: As long as the optimal discharging power p_S is higher than the exogenous storage capacity P_S it holds that $p_S = P_S$. Then the marginal value of wind capacity is solely a function of the increased demand level at night $L_N + P_S$ and the optimum wind capacity can readily be derived from the condition $c_W = mv_W$:

$$\begin{aligned} c_W &\stackrel{!}{=} mv_W = 4380cf_N mc_{N,s} = 4380cf_N(L_N + P_S - cf_N P_W^A) dm_{c_{cg}}/dp \\ \Rightarrow P_W^A &= \max \left\{ 0, \frac{1}{cf_N} (L_N + P_S) - \frac{1}{4380cf_N^2} \frac{c_W}{dm_{c_{CG}}/dp} \right\} \end{aligned} \quad (3.4)$$

Case B: If more storage power capacity is available than needed, also the transferred hourly energy is subject to optimization. This case is equivalent to the optimization of an investment in storage capacity at zero capital cost, i.e. the marginal cost for charging during the night is equal the marginal revenue from selling the discharged energy during the day. At the same time the wind power capacity is optimized as above:

$$\begin{aligned} 0 &\stackrel{!}{=} mv_S = 4380(\eta mc_{N,s} - mc_{D,s}) \\ c_W &\stackrel{!}{=} mv_W = 4380cf_N mc_{N,s} \end{aligned} \quad (3.5)$$

The two equations 3.5 form a linear system which can be solved for the installed wind power capacity P_W and the charging power p_S :

$$\begin{aligned} P_S^B &= \max \left\{ 0, \frac{L_D}{\eta} - \frac{1}{cf_N \eta^2} \frac{c_W}{4380 \text{ d}mc_{cg}/dp} \right\} \\ P_W^B &= \max \left\{ 0, \frac{1}{cf_N} \left(L_N + \frac{L_D}{\eta} \right) - \left(1 + \frac{1}{\eta^2} \right) \frac{1}{cf_N^2} \frac{c_W}{4380 \text{ d}mc_{cg}/dp} \right\} \end{aligned} \quad (3.6)$$

The optimal wind power capacity thus increases linearly with the installed storage power capacity in the regime A. When the marginal value from the transfer is zero, the wind capacity and the charging power reach the saturation levels defined by the equations 3.6. In all cases the capital cost of the wind enters the equations as a fraction of the slope of the marginal cost curve, which illustrates that the additional wind turbines compete with the running costs of the conventional generators.

In both cases the wind capacity $P_W^{A/B}$ is thus determined by

- a) a first term describing the wind capacity necessary to cover all of the system's respective load (limited by P_S in case A), minus
- b) the second term describing the relative economic performance of the wind turbines compared to the conventional generators, scaled by a factor comprising the round-trip efficiency and the capacity factor¹.

In the saturated regime where the amount of energy transferred from the night hours to the day hours is optimal, the marginal prices of electricity during the two time slots can be calculated by combining the equations 3.4 and 3.6. This yields the simple result

$$mc_{N,s}^B = \frac{c_W}{cf_N} \quad \text{and} \quad mc_{D,s}^B = \frac{c_W}{cf_N \eta}, \quad (3.7)$$

which illustrates the balance of the capital cost of wind power with the generation cost from the conventional generators in the unconstrained system.

3.3 The Model B³

A more complicated case is the competition between wind and solar power. As discussed in chapter 5.2, the main determinants of the relative capacity additions are given by the specific total capacity factors of the resources and their respective degree of matching with the demand profile. To account for these more complex mechanisms, three time slots per day are considered, characterized by the following capacity factors and demand levels:

¹It is interesting to note that both the capacity factor of wind power and the round-trip efficiency of the storage have a competing effect on the viability of wind power and storage: A higher cf_N increases the value of the wind turbines at a given marginal price of electricity during the day (more output per capacity), yet simultaneously erodes that same price (less revenue per output). Similarly, a higher η increases the value of storage (per energy sold during the day per unit charged at night), yet decreases the revenue per unit sold during the day. However, as these parameters are typically fixed this is of no further concern.

	Slot 1	Slot 2	Slot 3
Approximate time	1 am–9 am	9 am–5 pm	5 pm–1 am
<i>cf</i> wind	1	0.23	0
<i>cf</i> solar	0	0.79	0
Load [GW]	25	30	35

The most essential properties of the system’s assets are thus in agreement with the comprehensive Model A³¹²⁵. This includes first and foremost

- the higher capacity factor of wind power when compared to solar power (which translates to a lower levelized cost of electricity)
- the higher correlation of solar power with demand, when compared to wind power
- the diurnal variation of the load level.

Apart from the expansion to three time slots, the Model B³ is identical to B². The capacities of the wind turbines and the photovoltaic generators are subject to optimization; the yearly equivalent capital cost for photovoltaics is set to of $c_{pV} = 130,000 \text{ \$/MW/yr}$. The round-trip efficiency of the storage is equal to 0.5. The maximum power transferable by storage is set exogenously. The optimum of the actual charging and discharging power are assessed.

Due to the increased complexity of the model the analytical results are not presented here. A non-linear numerical solver was used to find the least-cost system state. The description of the results and a comparison to the Model A³¹²⁵ are provided in section 5.7.

Chapter 4

Base Scenario Parameters

4.1 Capacity Availability and Generator Operation

Data on the generator fleet installed in the system in 2014 is provided by the California Energy Commission [45]. Some further input was used to disaggregate the gas-fueled plants [46] and the hydro/pumped hydro storage plants [47]. Planned retirements until 2020 (especially relevant for natural gas fired plants) were extracted from datasets provided by the EIA and subtracted from the initial capacity [48]. Together with the generator lifetimes in table 4.1 this yields the final composition of the generator fleet in the reference year 2020. Most importantly, the geothermal plants are assumed to reach the end of their lifetimes until that year.

Depending on the technology, constraints apply to the yearly electricity production (expressed either directly or through the maximum capacity factor), the installed power capacity, or both:

- The yearly output from the **biomass**-fueled power plants is constrained due to the limited fuel availability. The maximum total yearly output is taken as roughly 30.7 TWh/yr, based on the availability of bone dry biomass [49] and the generator efficiency 0.32.
- The limited capacity factor of the **nuclear** power plants due to forced and planned outages was taken into account in a similar manner by restricting the yearly energy output to the nominal capacity times a capacity factor of 0.926, based on the data provided by the California Energy Commission [45]. The installation of additional nuclear power capacity is not allowed. This is based on the observation that no new plants are being planned in the western part of the United States [50].
- Some technologies are favorable due to their low costs while being constrained in their availability due to external factors. This is the case for the finite **geothermal** resources, which ultimately set an upper limit to the power capacity of the corresponding generators. While the assessment of the total potential is a complex undertaking, the California Energy Commission estimates that 4,000 additional MW

of geothermal power capacity could be installed in the state if the available resources were to be fully exploited [51]. This value is used in the model, resulting in an upper limit of 6.703 GW when including the initial endogenous capacity.

- The maximum capacity factor $cf = 0.391$ of **hydropower** plants has been calculated from 2013 data provided by the California Energy Commission [45]. The monthly fractions of the inflow are based on the runoff data reported by Madani *et al.* for low elevation hydroplants [52, figure 1]. The highest level of energy storable in the reservoirs is set to the maximum inflow fraction 0.203 in May times a factor 0.934, derived from the data provided by Madani *et al.*

4.2 Hourly Input Data

A complete set of historic hourly load data is available from the Californian ISO (CAISO) Open Access Same-time Information System (OASIS) [53]. Data on the collective hourly output from the Californian photovoltaic and solar thermal electricity generators was retrieved from the CAISO Daily Renewables Watch [54].

Four distinct wind sites were chosen and are modeled as separate technologies. This serves to capture the potential complementarity of the wind patterns at different sites and to allow for some system optimization in this regard. However, it has been found that the site with the highest average capacity factor takes on a dominant role and experiences the largest development. The data was obtained from the *Western Wind Resources Dataset* [55]. The choice of the specific locations is based on the distribution of the largest volumes of wind resources within the state.

4.3 Properties of Technologies

4.3.1 Dispatchable Generators

The costs associated with the installation and the operation of the electricity generators determine the operation and expansion of the system and are thus of paramount importance. The corresponding parameters have been gathered from various sources [45, 46, 49, 56–62, 62–64] and are summarized in table 4.1. In general, large ranges of suggested values have been found, especially for the per-megawatt installation cost of power plants. Some of the references [59] present a collection of values. In this case a median based on these values could be used. Otherwise the reference to a source reporting a typical value is given. The escalation rates of the fuel prices—where applicable—are based on the intermediate “reference case” scenarios of the U.S. Energy Information Administration [57]. The lifetimes of the generators are subject to large inconsistencies in literature, partly due to the mixed use of technical and economic lifetimes. The values listed here are supposed to represent the technical lifetime and have been inspired by a comparison of the assumptions in various major energy models, reported by the National Renewable

Energy Laboratory [64].

The California Energy Commission provides a list of the natural gas fired power plants taken out of operation between the years 2002 and 2006 [65]. As there is a clear (positive) correlation between the plant size and the age at retirement, a capacity-weighted average lifetime of 42 years was calculated and assigned to this technology.

The production of electricity from coal has become a marginalized practice in California (with a decrease from 593 MW to 275 MW between 2007 and 2014 [66]) and is destined to be phased out due to the Emissions Performance Standard described in section 2.1. It should be noted that part of this decrease was the result of a conversion to biomass-fueled power plants (132 MW) [66]. However, this option is not included in the model.

California's only remaining nuclear power plant *Diablo Canyon* is licensed to operate until 2024 [67]. Its owner and operator *Pacific Gas & Electric* is convinced that a license renewal beyond this date would hold great benefits for California [67]. Therefore, the technical availability of the facility is assumed to extend beyond the relevant time horizon of the model.

	Geo-thermal	Hydro	Nuclear	Coal	Biomass	NGCC	Natural Gas
Fuel price [\$/MWh]	-	-	2.4 [56]	10.4 [56]	9.2 [49]	25.9 [58]	(Industry, assume 38 MJ/m ³)
Fuel price escalation rate [%/yr]	-	-	0	0.77 [57, p.40]	0	3.15 [57, p.77]	(Reference case)
Overnight capital cost [\$/kW]	2,980 [59]	3,150 [59]	5,530 [60]	3,000 [60]	3,300 [59]	917 [59]	610 [59]
Fixed O&M cost [\$/kW/yr]	169 [59]	20 [59]	93 [60]	34 [60]	87 [59]	13 [60]	7 [60]
Variable O&M cost [\$/MWh]	0 [60]	0 [60]	2.1 [60]	4.5 [60]	5.3 [60]	3.6 [60]	10.4 [60]
Efficiency	-	-	0.33 [61]	37.9 [62]	0.32 [63]	0.50 [62]	0.31 [62]
Base year capacity [MW]	2,703 [45]	11,082 [45, 47]	2,323 [45]	174 [45, 48]	1,128 [45]	19,185 [46, 48]	28,954 [46, 48]
Lifetime [yr] [64]/see text	35	60	50	45	45	40	40
Age of base year capacity [yr] [68]/see text	30	0	0	30	15	25	25
Capacity factor base load generators	0.92 [69]	0.39 [69]	0.93 [69]	1	1	1	1

Table 4.1

Cost and operational parameters for the dispatchable power plants.

4.3.2 Variable Electricity Sources

The data mining on the variable electricity sources was performed in a similar way as described above. Since further capital cost decreases are expected for technologies harvesting wind and solar energy, these values were projected to 2020 based on predictions in various references [70, 71]. The maximum capacity of wind power is limited to 34,110 MW, based on estimates of the total in-state availability of this resource by the National Re-

newable Energy Laboratory [72]. In the case of solar photovoltaics some sources provide detailed information on the differences in costs depending on whether the panels are used in a residential, commercial or industrial context [73]. In this case the cost at the lower end of the range was used.

	Solar PV	Wind	Thermal solar
Capital cost 2015 [\$/kW]	2100 [74, p92 (utility)]	2000 [74, p63]	5000 [71, p23]
Capital cost escalation rate [%/yr]	-2.8 [70, p.23 (BNEF data)]	-0.74 [75, p23]	-1.69 [71, p23]
Capital cost floor [\$/kW]	1475 [70, p.23]	1300 [75, p23]	2500 [71, p23]
Capital cost 2020 [\$/kW]	1518	1913	4440
Fixed O&M cost [\$/kW/yr]	30 [59]	24 [59]	62 [76, p24]
Base year capacity [MW]	3072 [69]	6205 [69, 77]	363.8 [78]
Life time [yr] [64]/see text	30	25	30
Age of base year capacity [yr]	0	5 [68]	5 [78]

Table 4.2

Cost and basic operational parameters of the intermittent electricity sources.

4.3.3 Storage Technologies

The parameters of the storage technologies are based on a literature review whose detailed results are reported in the appendix. This research is obstructed by the scarcity of information on separate per-energy and per-power costs of storage: In most cases the energy-to-power ratio is explicitly assumed as being fixed or implicitly determined by the service associated with the reported storage type. The parameters finally used as input to the model are shown in table 4.3. Significant decreases of the capital expenditures are expected for some of the technologies and expressed through the change rate. The “E2P range” defines the minimum and maximum energy capacity allowed to be installed for a given power capacity. This reflects the technical reality and the different potential applications of the technologies. The DOD column contains the maximum depth of discharge, which is implemented as a reduced availability of energy capacity in the model.

It must be borne in mind that many of the relevant input parameters are effectively dependent on the specific application of the respective storage technology, which in itself is a result of the optimization (for example, the frequency of the charging cycles are known to affect the technical lifetime) [79]. While an iterative approach could be chosen to take this complication into account, it was not considered at this stage.

4.3.4 Other Exogenous Parameters

The future annual demand in the Californian power system has been estimated in a study published by the California Energy Commission. In the model a constant average increase of 1.13%/yr is used, based on the mid energy demand scenario [80, p.2]. It serves to project the 2014 demand to the reference year 2020.

The choice of the discount rate follows the EIA Annual Energy Outlook 2014, where a technology-independent real after tax weighted average cost of capital of 6.5% is used to calculate present values, costs and capital recovery factors [81, p2].

Type	Capital Cost [1/kW]	Capital Cost [1/kWh]	Change Rate (P/E) [%/yr]	O&M [\$/yr/ kW]	VC [\$/ MWh]	Eff.	LT	Energy Loss [1/h]	DOD [%]	E2P Range [h]
Li-Ion	305	600 [8]	-3.8/ -7 [8]	5	7	0.87	15	8e-5	80*	1-24
NaS	305	415	-3.8/ -3.3	5	7	0.75	15*	0*	80	1-24
Pb-Acid	305	550	-3.8/ -3.3	5	7	0.8	10	5e-5	60	1-24
Redox- Flow	1416	215	-3.5/ -4.3	41.5 (-9%/yr)	1	0.65	20	0	100	1-24
CAES	1000	3	-1.7/ +0.0	7	3	0.5	35	3e-4	90*	4-96
Flywheel	1362	148	-5.7/ -2.5	18	1	0.85	20	0.1	75	0.1- 1
P-Hydro	1750	10	+0.9/ +0.0	4.6	4	0.8	50	5e-6	90	4- 168

Table 4.3

Cost and basic operational parameters of the storage technologies. This data is based on the more extensive data collection in the appendix, unless a specific reference is given.

4.4 Scenarios

The analysis in the following chapter is based on two distinct sets of scenarios: First, to gain a first fundamental understanding of the system's properties, the cost effective state of the system under the projected real-world assumptions has been analysed, as described in section 5.1. This especially includes first and foremost an initial pumped hydro capacity endowment of 2.8 GW and a carbon cost of 17 \$/t_{CO₂}, roughly corresponding to the floor value of the emission allowances in 2020.

Second, the impact of the price of CO₂ emission allowances and increasing levels of storage on the optimal composition and operation of the system was investigated by sweeping the former between 0 and 120 \$/t_{CO₂} and the latter between 0 and 10 GW of storage power capacity. In contrast to the base scenario described above, the pumped hydro storage was not included in the system to avoid any offset from the already present storage capacity. Within this constraint on the total capacity the least-cost composition of the storage fleet is chosen. More than 30 GW of storage have been found to be a part of the least-cost system in the *SWITCH model* described in section 2.2. Since California hosts about 30 % of the WECC's capacity, the upper limit of 10 GW appears to be a reasonable choice in this light.

A fundamental decision in the modeling approach consists in the introduction of storage through either a constraint on the minimum total capacity (energy or power) or an assumption on a decrease in the capital cost of the various technologies, causing them to become part of the system's least-cost state. While the cost decrease is more realistic in the long-term development of the system, this approach is less practical if only a single representative year is considered. In this case the balance between different storage technologies would be mainly affected by the highly uncertain assumptions on the future development of the costs. Furthermore, setting the total amount of storage (power)

capacity endogenously is in line with the corresponding policy recently implemented in California (see section 2.1).

Chapter 5

Results and Discussion

5.1 Least-Cost State of the Base Scenario

The analysis of the least-cost state of the base scenario (described in 4.4) allows for the assessment of the relative competitiveness of the different technologies, the seasonal variations of the system's operation and finally the properties of the storage's operation.

Technology Choice and System Composition

The composition of the system in terms of generator capacity is shown in figure 5.1a). The initial 2014 capacities were projected to 2020, which—within the limited temporal resolution of the model—leads to the retirement of the geothermal power capacity. However, due to the high competitiveness of this technology the maximum possible capacity is part of the least-cost solution. Apart from this, as the total installed capacity exceeds the planning reserve margin, some of the gas-fueled peak capacity is removed to avoid the fixed O&M costs. It should be noted that an overwhelmingly large part of the natural gas power plant capacity kept in the system serves the sole purpose of meeting the reserve margin constraint. Very large amounts of additional wind power capacity at the location 4 are found to be a viable system component, complemented by smaller amounts wind capacity at location 1.

While the maximum capacity of nuclear power and the yearly energy output from biomass-fueled plants are limited exogenously, these constraints are not binding. Additional hydro and geothermal power capacity, in contrast, would lower the total system cost.

To some extent, the preference for certain types of technologies can be understood from the capacity factors and the levelized costs of electricity (LCOE) in figure 5.2. Their high capacity factor (limited exogenously to 0.92) in combination with its effective lack of variable costs make geothermal generators strongly favorable from an economic viewpoint. The total capacity of this technology is thus only limited by the availability of sites appropriate for development. Similarly, wind power at the location 4 delivers high output

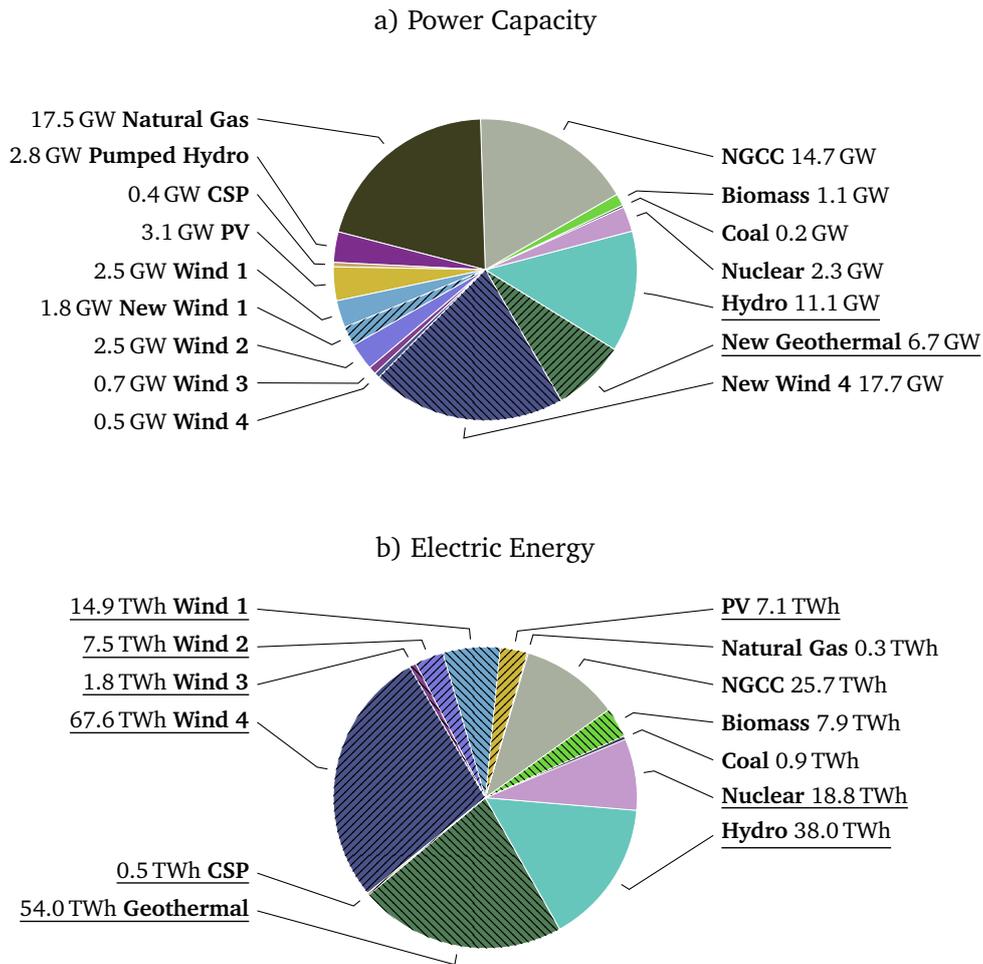


Figure 5.1

a) Installed capacity in the 2020 base scenario. The hatched wedges correspond to newly installed capacity. **b)** Energy produced in the 2020 base scenario. Hatched wedges correspond to energy eligible to contribute to the RPS target. Underlined labels mark technologies which are actively constrained in capacity additions and/or energy output (which is trivial in the case of (free) electricity from variable sources).

at relatively low capital cost.

The conventional natural gas plants have a capacity factor close to zero, causing the average LCOE to be orders of magnitude larger compared to the other technologies. Their presence in the system is thus primarily justified by the shadow price of the planning reserve margin. The LCOE of the CSP plants amounts to a total of 30.7 ¢/kWh, reflecting the high capital costs combined with a relatively low capacity factor due to the dependence on direct solar radiation.

Figure 5.1b) shows the electricity mix in the base scenario (2020). It is especially the high competitiveness of wind and geothermal power that puts a large weight on renewable sources as a whole and causes the RPS not to be a binding constraint. This is the case for all scenarios presented hereafter.

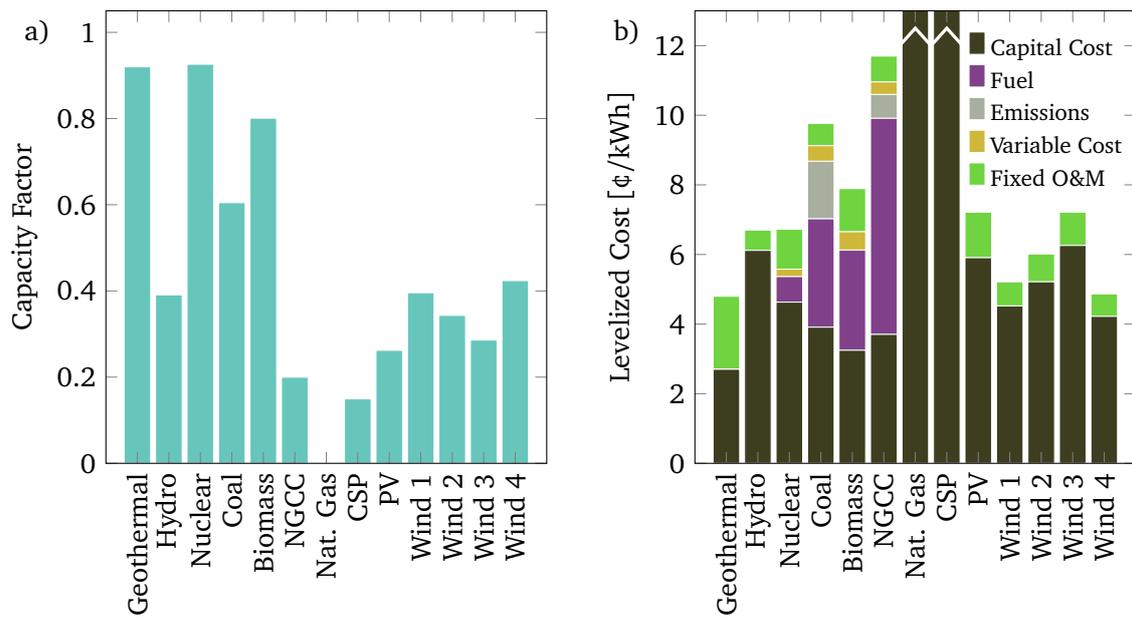


Figure 5.2

a) Capacity factors and **b)** levelized costs of electricity from all technologies. Especially in the case of wind power at location 4 the competitiveness is a direct consequence of the turbines' high capacity factor. The LCOEs of CSP (due to the high capital cost) and conventional combustion turbines (due to the small capacity factor) are much higher than the upper limit of the y-axis' scale.

Monthly Marginal Cost Variations

The monthly average marginal electricity price levels throughout the year are shown in figure 5.3b): They reach a minimum between March and May, to then climb to their maximum value in August. The high prices in summer are driven by the excessive use of the NGCC generators (and even the very expensive conventional gas power plants) to provide marginal electricity in summer and fall, which can be avoided during spring time (see plot a).

In detail, the reason for this dependency can be summarized as follows:

- The **water inflow to the hydroelectric power plants** shows an especially large monthly dependence (figure 5.3c). The restriction on the maximum storage capacity of the impounding reservoirs is actually binding in the month of June following the spring flood: Larger reservoirs would allow more energy to be transferred to the high-demand months of summer and fall. Together with the other operational constraints described in section 3.1 this results in a good agreement of the monthly average hydropower output with the scaled monthly output of the corresponding plants in the real system (orange dots).
- Similarly, the largest contributions from the dominating **wind power** site occur during the early months of the year, with a gradual decrease over the summer months until October (see figure 5.3d). Compared to these relative changes, the monthly electricity produced from solar photovoltaics is rather constant throughout the year. The energy contributions from concentrating solar power are negligible.

- The largest **electricity demand** occurs in the summer months around July, when the base load demand reaches a maximum and the daily load profile shows a pronounced peak during the afternoon.

Altogether, these system properties lead to a rather strong mismatch between electricity demand and the supply of energy with low variable cost. This causes the variance in the marginal cost mentioned above. These seasonal variations also cause the significant differences in the contributions to the value of the assets discussed in section 5.2ff.

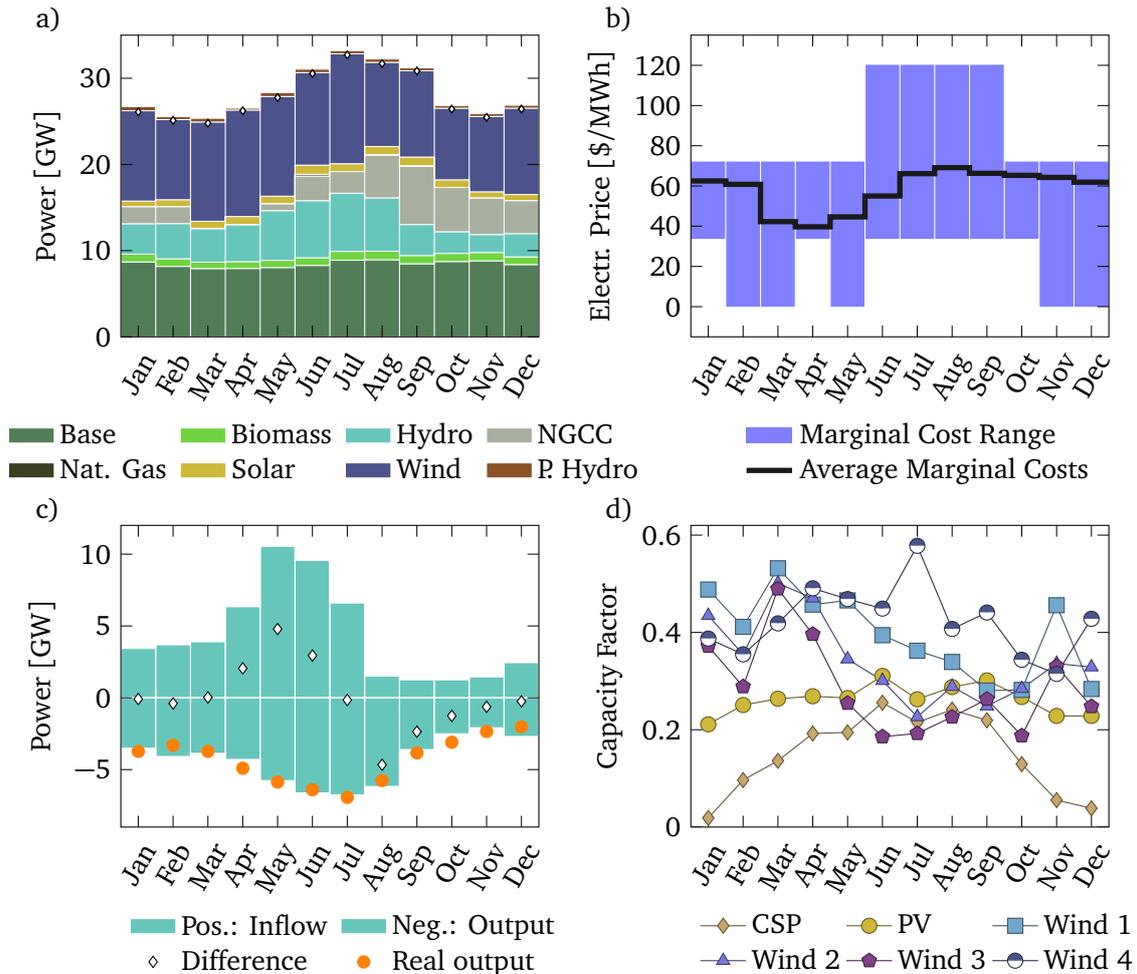


Figure 5.3

a) Monthly average output of all generators; **b)** average marginal cost (solid line) and range of the marginal cost levels; **c)** inflow to and operation of the hydro power plants, compared to the normalized output of the real-world power plants; **d)** monthly capacity factors of all variable technologies.

Use of the Pumped Hydro Storage

Despite the seasonal mismatch between supply and demand the available 2.8 GW of pumped hydro storage are not used over such long time scales. Figure 5.4a) shows the

monthly time-averaged input and output to and from the storage. Losses due to the limited round-trip efficiency were subtracted from the charging power (shown as negative values). The difference between charging and discharging is close to zero for all months, which means that energy is used during the same month it was charged. Any deviation from this is a consequence of intra-weekly charging/discharging events during the months' respective last or first days.

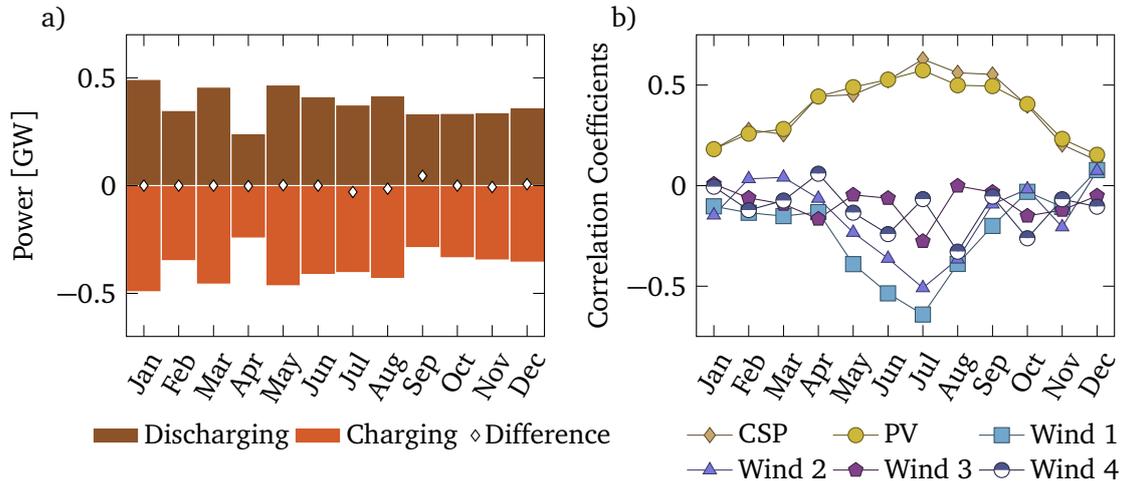


Figure 5.4

a) Average charging and discharging power. As the difference is close to zero the storage is only used to transfer energy within single months. **b)** The monthly correlation coefficients of the variable power sources with demand show a strong monthly dependence.

The same monthly variations which affect the monthly average marginal cost level described above can also be expected to cause large seasonal variations in the use of the available storage. Furthermore, the monthly correlation coefficients between the wind/solar output and the load profile show pronounced changes throughout the year (figure 5.4b). These fluctuations in the quality of the matching between demand and supply equally influence the storage operation.

The average dispatch during the working days of two typical months during summer and winter is shown in the figures 5.5a) and b). A pronounced peak during the afternoon causes a significant increase in the demand for power during summer. Furthermore, the average daily output from the wind turbines shows a minimum during those exact same hours. While the relatively high (yet constrained) availability of hydropower assists in the mitigation of this mismatch, the NGCC power plants are being relied upon to produce large amounts of electricity. Consequently, the storage is consistently used to cover the demand at the very peak of the daily load profile. This is in contrast to the winter months, where discharging can occur during almost any hour of the day.

This is shown with greater clarity in the plots c) and d): In summer the average daily charging/discharging power is consistently zero during the evening/at night, respectively. In January, this preference is much weaker.

On an hourly basis this seasonal dependence of the use of the storage is shown in the plots e) and f). In July the much more steady wind patterns together with the afternoon peak of demand result in a very regular effective load profile. This allows for the consistent diurnal cycling of the storage. In January more extended periods of calms are experienced,

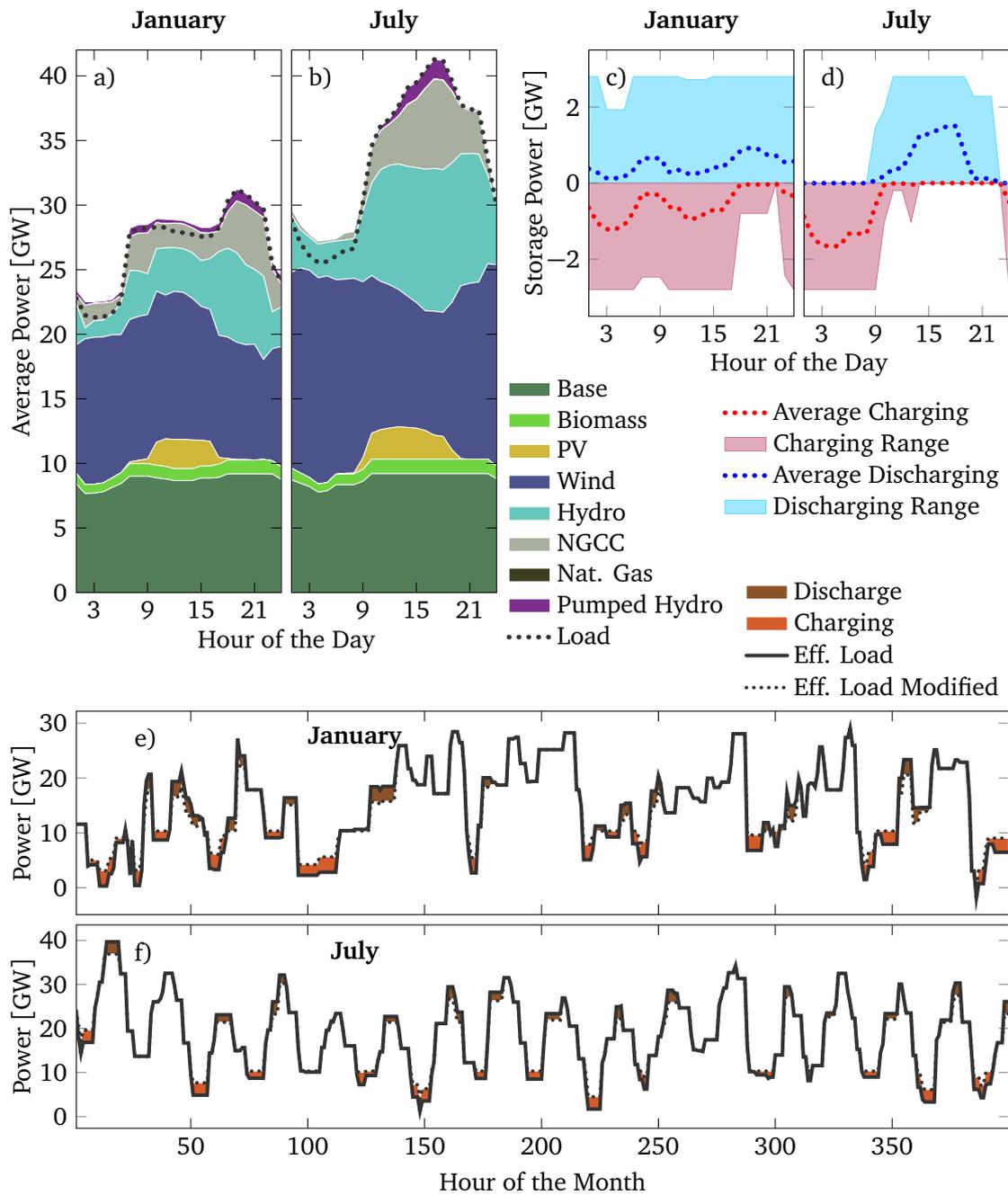


Figure 5.5

Varying use of the pumped hydro storage during different seasons: **a)** and **b)** show the average dispatch during the working days (Monday-Friday) in January and July, respectively. The primary difference is the lack of a pronounced afternoon peak in July, which reduces the preference for the charging and discharging during specific hours. Also, the average wind power output in July shows a dip in the afternoon, which exacerbates the variation of the effective load. **c)** and **d)** show the average charging/discharging power as well as the respective ranges. The much higher regularity of the diurnal charging and discharging cycle in July is evident. An example for the hourly modification of the effective demand curve is shown in the plots **e)** and **f)**. While the storage is charged consistently at night in July to release energy during the day hours, the effective load profile (and therefore the operation of the storage) is much more irregular in January. *Base* is the sum of Nuclear, Coal, and Geothermal power.

which causes energy to be stored for longer periods of time.

Summary

The composition of the system is largely determined by the generators' levelized cost of electricity and the initial capacity endowment. The high competitiveness of geothermal and wind power causes a dominance of emission-free technologies, which makes the RPS constraints non-binding in all scenarios.

The large monthly variations of the hydro power inflow cause stark seasonal fluctuations of the average marginal price of electricity. This is exacerbated by the high penetration of wind power and the seasonal dependence of its hourly production profile, as well as the changes in electricity demand throughout the year.

While the system's pumped hydro storage is not used to mitigate these seasonal variations, its operation shows a clear dependence on the load and wind profiles, with a large difference between summer and winter.

5.2 Varying Storage Capacity and Cost of CO₂ Emission Allowances

The impact on the least-cost state of the system of the carbon cost (between 0 and 120 \$/t_{CO₂}) and the storage capacity (between 0 and 10 GW) has been investigated. The composition of the system in terms of installed capacity (left) and produced energy from different technologies (right) is shown in figure 5.6. The case for unaccounted carbon emissions (top) is compared to the scenario including a cost of 120 \$ per metric ton of CO₂.

The effects of the increasing storage capacity in this configuration are rather subtle and largely concealed by the bulk operation of the system. Especially the technologies providing the cheapest base load (geothermal generators, hydro and nuclear plants) are not affected by storage at all. The same holds for the intermittent sources with low capacity factor (wind 2-3 and concentrating solar power), where the initial capacity endowment just serves to provide free electricity for the rest of the lifetime (apart for some minor fixed expenses on operation and maintenance).

The main changes in this representation can be summarized as follows:

- The most obvious change for both emission cost scenarios is the replacement of peak capacity as storage covers a larger share of the total planning reserve requirement; however, this does not affect the system's operation.
- In the absence of a cost on carbon the only noticeable effect is a small shift between the output from different wind sites (not shown).
- In contrast, in the 120 \$/t_{CO₂} scenario the increasing storage capacity leads to a reduction of the NGCC and biomass power plant capacity, a strong overall increase in wind power output, and the employment of two different types of storage at higher

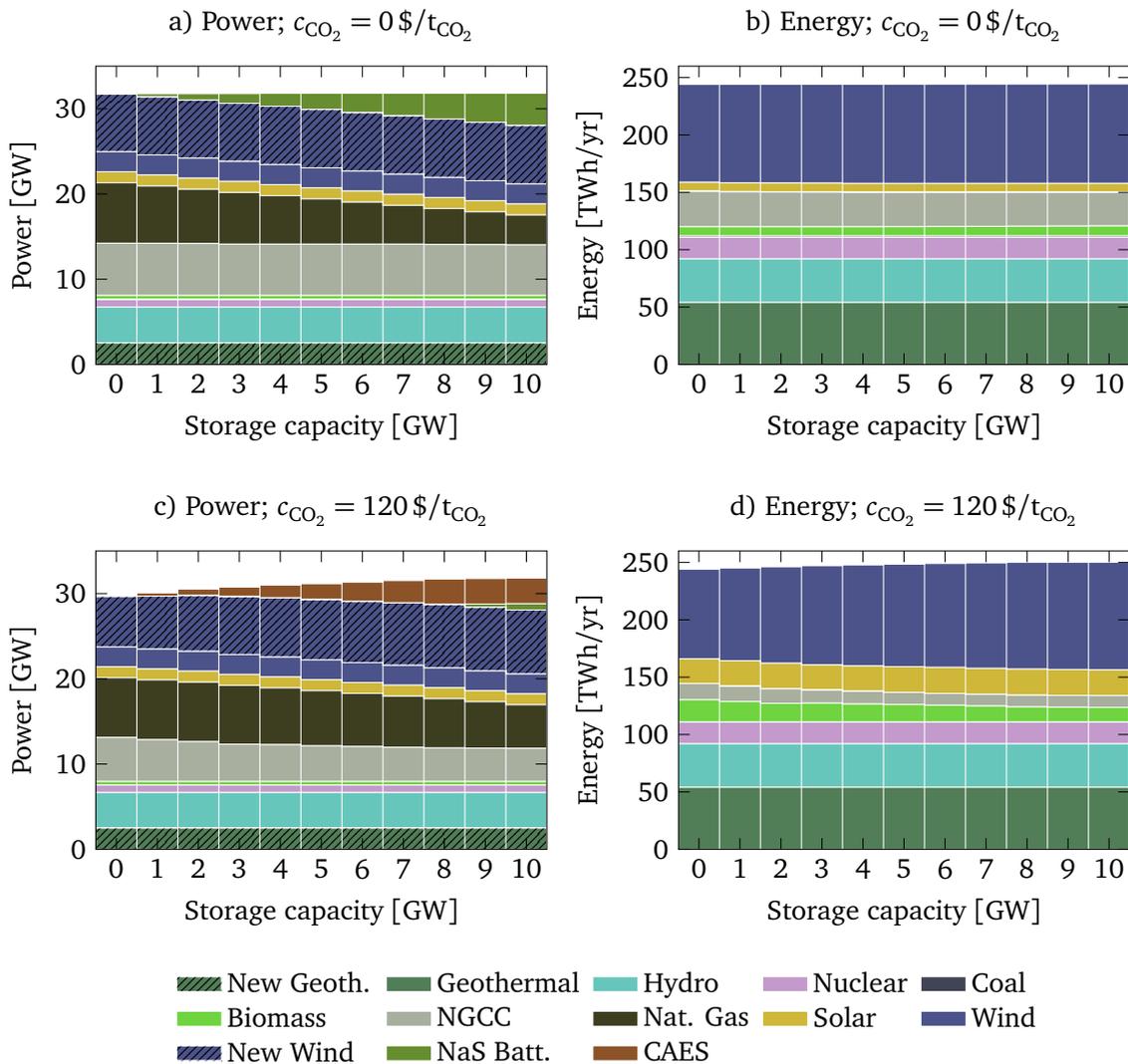


Figure 5.6

Installed power capacity and produced energy in dependence on the total storage capacity, for a)/b) the lowest and c)/d) the highest considered cost on carbon emissions. The replacement of conventional natural gas power plant capacity is due to the storage's contribution to the reserve margin constraint. Other changes are generally more subtle.

levels.

It must be noted that the total system cost increases for all storage capacities higher than zero, i.e. the addition of storage capacity is not part of the least-cost state of the system. It can be shown that only for excessive CO_2 emission prices of $180 \text{ \$/t}_{\text{CO}_2}$ or more would the value of small amounts of storage exceed the associated total investment and operation expenses.

In the remainder of this chapter the interactions of the storage capacity with the system are identified and analyzed in more detail. Figure 5.7 provides an overview of the selected effects:

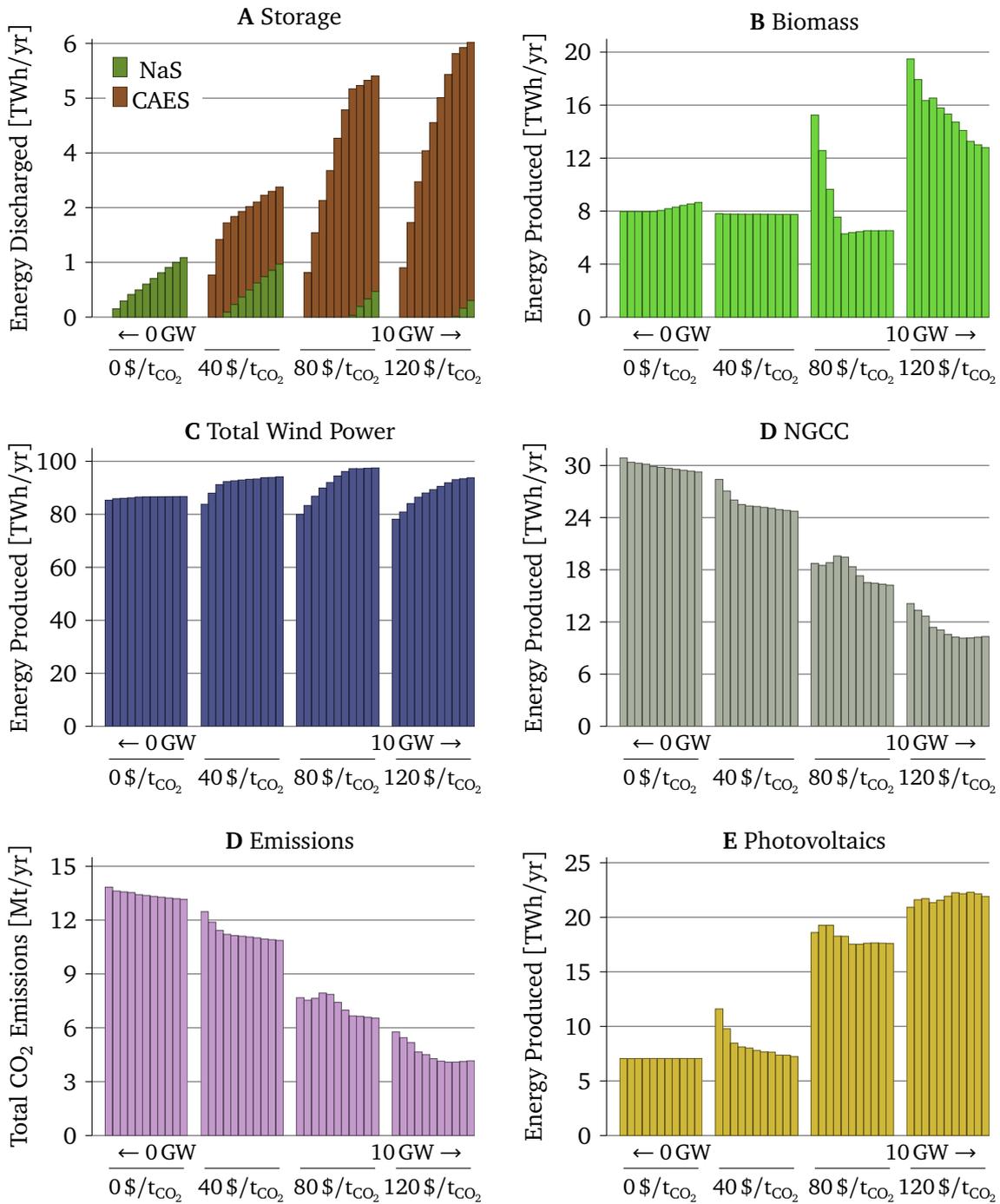


Figure 5.7

Effect of varying total storage capacity under different carbon prices on various variables. The selected observations discussed in the text are **A**: The changing composition of the storage fleet with increasing emission costs; **B** the qualitatively diverse impact of storage on the electricity generation from biomass power plants, depending on the cost on carbon; **C** the consistently increasing wind power capacity for higher storage capacities, as well as the decreasing capacity for increasing carbon costs in the absence of storage; **D** the small increase in NGCC capacity (resulting in an increase in total CO₂ emissions) at 80 \$/t_{CO2}; and **E** the qualitatively diverse impact of storage on the optimal PV capacity: decreasing for low, increasing for high carbon costs.

- A The **changing composition of the storage fleet** reflects the changing use of this technology class.
- B The **energy output from the biomass power plants** shows a diverse dependence on both parameters: for zero cost of carbon additional storage favors the electricity production from this generator type; higher carbon prices make this technology more competitive, yet enables storage to erode its contribution to the electricity mix rather strongly.
- C The **total wind turbine capacity** is consistently favored by higher levels of storage capacity. Thereby, higher costs on carbon emissions provide a counteracting effect which leads to smaller capacity additions in the absence of storage.
- D While the aim of the price on carbon emissions consists in the provision of incentives for the electricity production from clean sources, the effect of this instrument is partly eroded by higher storage capacities for some specific parameter combinations: For a CO₂ emission cost of 80 \$ per ton the **output from the combined cycle plants** sees a 5.8% rise as the storage capacity increases from 1 to 3 GW, leading to a net increase in total carbon emissions by almost the same relative amount. This happens while the capacity of these plants is largely unaffected.
- E **Solar photovoltaics** is generally supported by higher costs of emission allowances. However, also in this case the qualitative impact of higher storage levels changes with the carbon price. The strong monotonous decrease for 40 \$/t_{CO₂} is somewhat counter-intuitive, as PV could be expected to benefit from the possibility of using its stored output during the evening peak.

5.3 OBSERVATION A: Choice of Storage Technology

The composition of the storage fleet depends on both the cost on carbon emissions and the total power capacity of storage. The specific technology choice is thereby determined by the value of the energy and power capacities in the least-cost state. The total cost in units of dollar per kW of *discharge* capacity of the individual storage technologies in dependence on the energy-to-power ratio is shown in figure 5.8. From this representation it is clear that in the case of a small demand for energy capacity, sodium sulfur batteries are the most cost effective solution, while for higher demand compressed air energy storage will be the technology of choice. The details of the competitiveness will depend on the actual use of the technologies and the incurred hourly leakage losses. This does, however, not affect the qualitative validity of this result within the framework of the Model A³¹²⁵.

In the scenario without a cost on carbon emissions the charging cycle is mainly driven by diurnal replacement of output from the NGCC peaker plants. This small-volume operation happens with high frequency and relatively high regularity, as shown in the top panel of figure 5.9.

The scenarios with non-zero costs on carbon emissions see a predominance of CAES. This is a consequence of the fact that only for $c_{\text{CO}_2} \geq 40 \text{ \$/t}_{\text{CO}_2}$ is it economically feasible to transfer energy between the marginal cost levels corresponding to the variable cost of

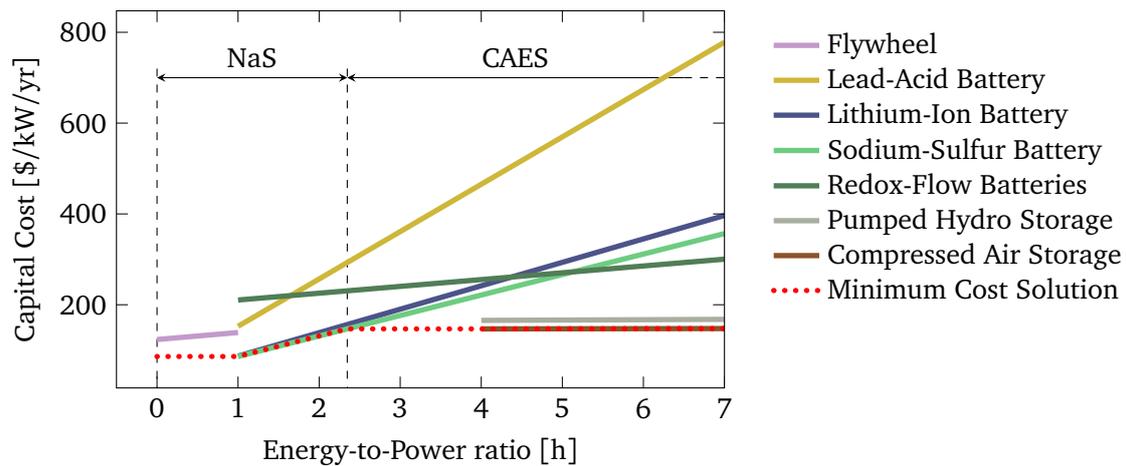


Figure 5.8

Approximate total cost of the different storage technologies for varying energy-to-power ratio. The data is limited to the allowed E2P-ranges of each technology.

The E2P range is divided into two regimes: Sulfur batteries provide the least-cost power capacity if the demand for energy capacity is low. For higher E2P values compressed air energy storage takes over. The hourly energy loss is not taken into account in this representation. Given the poor value of this parameter for CAES, a relative loss of competitiveness can be expected for this technology, which, however, does not affect the final composition of the storage portfolio, as shown by the results of the Model A⁵¹²⁵.

the biomass and the NGCC power plants. The rise of the biomass capacity for scenarios with a higher cost on carbon leads to the replacement of NGCC output and makes the biomass plants the marginal generators e.g. during a large part of spring. This avoids the daily operation of the NGCC plants to cover the peak load during many days. While this depends on the variation of the effective load, the result is the much more irregular marginal cost and charging state profiles shown in figure 5.9. It is this irregularity that puts a higher value on the energy capacity and justifies the switch to CAES.

The specific roles of the two technologies can thus be summarized as follows:

- **NaS batteries** are employed when the charging and discharging occur with a high frequency and between similar electricity price levels, which makes a small amount of (expensive) energy capacity and a high round-trip efficiency most beneficial. It should be noted that the constraint on the minimum energy-to-power ratio is binding in this case, i.e. an even lower energy capacity would reduce the system cost.
- **CAES** is favored by the increase in both the amplitude and the period of the marginal cost variations. This justifies the switch to the technology with higher power capacity but lower energy capacity cost.

A combination of the two will eventually be the least-cost solution, as the marginal value from the use of the CAE storage decreases and NaS batteries constitute a cheap alternative to satisfy the residual power capacity constraint.

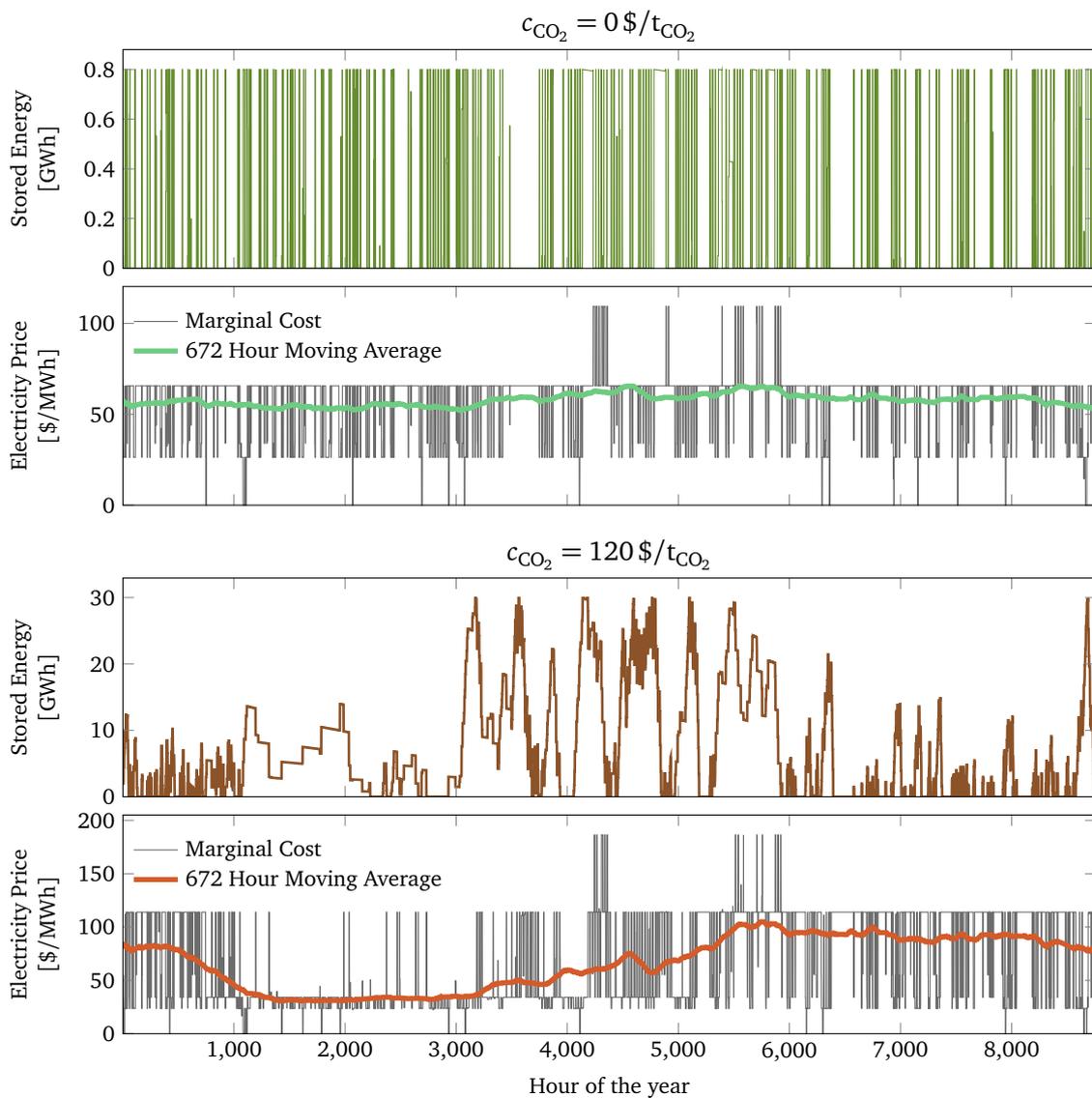


Figure 5.9

Qualitative comparison of the operation of the storage under two different costs on carbon for 1 GW of storage power capacity. The marginal cost profile in the case without a price on carbon emissions is rather regular, with daily variations between the variable cost of the NGCC generators and the marginal cost level corresponding to the expansion of wind power. As a consequence, the small amount of **NaS** storage energy capacity is used primarily for daily charging and discharging. At the highest emission cost of 120 \$/t_{CO₂}, the output from the NGCC plants is much more expensive. However, they are replaced by cheaper generators during many days of the year. This leads to significantly more pronounced variations of the electricity price profile and consequently of the charging cycle. **Compressed Air Energy Storage** is used in this case. Notice the large difference of the ordinate scale in the charging state plots.

5.4 OBSERVATION B: Increasing Generation from Biomass Plants at Low Carbon Cost

While no additional biomass power plant capacity is installed with increasing storage capacity if the cost on carbon is zero, the energy output of those power plants increases somewhat for higher storage penetration. This is a simple example for how the introduction of the storage capacity into the system leads to a *direct* optimization of the use of the available resources.

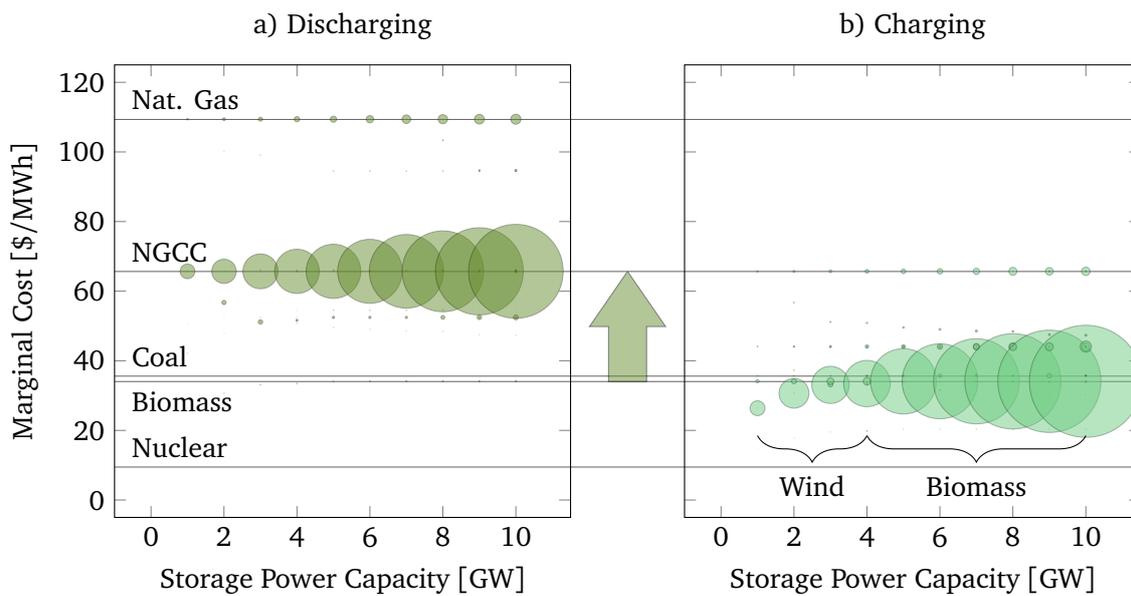


Figure 5.10

Marginal cost levels during **a)** the discharging and **b)** the charging of the storage. The areas of the circles are proportional to the total energy charged/discharged at the corresponding electricity price. The dominant marginal cost levels below the running cost of the biomass power plants correspond to the installation of additional wind power capacity, which leads to savings throughout the year. When the value of incremental wind power is not high enough to make this technology a cheaper alternative, the bulk of the charging takes place during hours where biomass plants provide the marginal electricity. This causes a rise in the output from this type of power plant as the storage capacity increases.

Figure 5.10 shows the operation of the storage (NaS batteries) resolved by the marginal cost level prevailing during those hours where the charging and discharging occur. The fact that some of the charging takes place at the same price levels as the bulk of the discharging is a consequence of the variations in effective load on a seasonal scale: Periods of high effective load in summer occasionally justify the charging of storage with electricity from NGCC plants to replace the output from the conventional gas turbines, which is made possible by the high round-trip efficiency of the NaS batteries.

To understand why the increasing employment of storage favors the production from the biomass-fueled generators it is important to note that this technology is the one with the lowest variable cost among those with capacity factor below their respective maximum. With this constraint on the cheaper production (geothermal, hydro, nuclear) the biomass

power plants provide the marginal unit of electricity during many hours of the year. At the same time the difference in variable cost compared to the NGCC plants is sufficiently large to justify the total cost of the energy transfer¹

$$\frac{1}{\eta_{\text{NaS}}} v c_{\text{BM}} + v c_{\text{NaS}} = 52.4 \text{ \$/MWh} < v c_{\text{NGCC}} = 65.7 \text{ \$/MWh} \quad (5.1)$$

with a margin large enough to include any losses due to the hourly leakage.² This is the reason why most of the charging at high storage capacity in figure 5.10b) occurs at roughly 34 \\$/MWh, the variable cost of electricity production from the biomass plants.

For storage capacities smaller than 5 GW, batteries are charged at a somewhat lower electricity price, which gradually increases to 34 \\$/MWh (see figure 5.10b). This cost level corresponds to the marginal build-out of wind-power: During the hours of peak electricity production from wind power a marginal increase in demand provides incentives to install additional wind capacity. This allows to lower the finite-cost electricity production during the rest of the year. With more storage in the system the demand during those hours increases further, causing an elevated amount of wind capacity to be part of the optimum system state (see figure 5.7C and section 5.5).

When the net value of the incremental wind build-out is sufficiently low, the increase of the production from biomass-fueled power plants becomes the least-cost option. It is thus a simple continuation of the provision of additional charging electricity during the minima of the effective load profile.

An example for the specific operational consequences of this effect on an hourly basis is shown in figure 5.11, where the biomass-fueled generators are run throughout some of the nights to charge the storage. The discharge then occurs during the daily demand peak to avoid the use of the NGCC plants.

Intuitively one might expect this effect to be all the more important at higher costs of carbon emissions, which provide a more pronounced incentive to replace electricity from NGCC plants with stored electric energy produced from biomass. However, this is not necessarily the case, and under some conditions the combined cycle plants become disproportionately more competitive. This is shown in section 5.6.

Summary

At zero carbon cost the increase of the storage capacity directly induces the increase of electricity production from the biomass power plants once the build-out of wind power has reached its maximum viable level. The stored energy serves to partly avoid the output from NGCC plants. This is made possible by the relatively high round-trip efficiency of the NaS batteries used in this scenario.

¹Note that this does not justify the *capital cost* of the storage, as mentioned above.

²In comparison, at this cost of carbon emissions the low efficiency of CAE storage would inhibit this replacement.

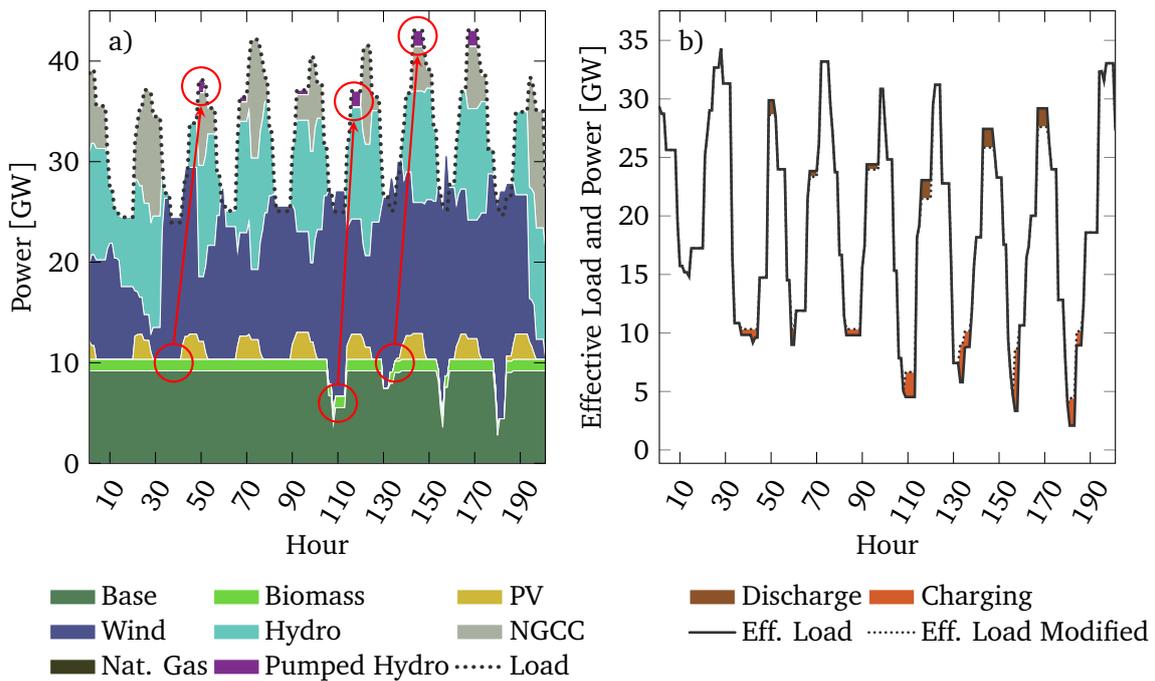


Figure 5.11

Example for the transfer of energy produced from biomass power plants from the night hours to the peak of demand. The biomass plants operate at full output to charge the storage (a). The final result is the increase of the effective load during the night and the peak-shaving during the day (b).

5.5 OBSERVATION C: Increasing Wind Capacity with Increasing Storage Capacity

Figure 5.7C shows that the increase of the storage capacity in the system consistently raises the marginal value of wind power, thus leading to a capacity expansion. While this is certainly in agreement with basic intuition, the exact causes are obfuscated by the complexities of the wind power profile, its correlation with demand, and the operation of the other generators. To gain a basic understanding of the underlying relations, the minimalistic complementary Model B² has been devised (see section 3.2):

With the optimal capacity expansion and operation during the two representative hours the wind power increases at a rate of $1/cf_w$ per gigawatt of storage, which simply indicates that all of the additional demand induced by the charging is covered by the build-out of wind turbines. This happens until the marginal cost during the day hour is lowered to $c_w(cf_w\eta)^{-1}$, i.e. the capital cost of wind power incurred to produce an additional transferred unit of electric energy. This effectively excludes additional wind power capacity from lowering the electricity prices during the day hour and marks the maximum storage charging power to have an impact on the system.

The Expansion of Wind Power

The addition of wind turbine capacity is a consequence of the increased demand from the charging of storage during the hours with the lowest effective load and will proceed as the corresponding marginal costs are lower than the variable cost of production of the next-cheapest power plant (see section 5.4).

The storage-dependent wind power capacities resulting from the models A³¹²⁵ and B² are shown in figure 5.12. The qualitative agreement is evident: A linear increase is followed by a plateau, which occurs at higher storage capacities for higher variable electricity production cost (carbon price) of the conventional generators in the system. In the two-hour model the slope $1/c_{f_w}$ depends solely on the capacity factor of the wind turbines. In the comprehensive model the slope is consistent for the scenarios with $c_{CO_2} = 80$ and 120 \$/t. For $c_{CO_2} = 40$ \$/t the stronger increase can be attributed to the initial competitiveness of solar photovoltaics, which quickly decreases for larger storage capacities (see figure 5.7E). At zero carbon cost a relatively high correlation between the marginal cost profile and the wind power output leads to a higher value of this technology when compared to the scenarios with higher carbon emission prices (as discussed in section 5.7).

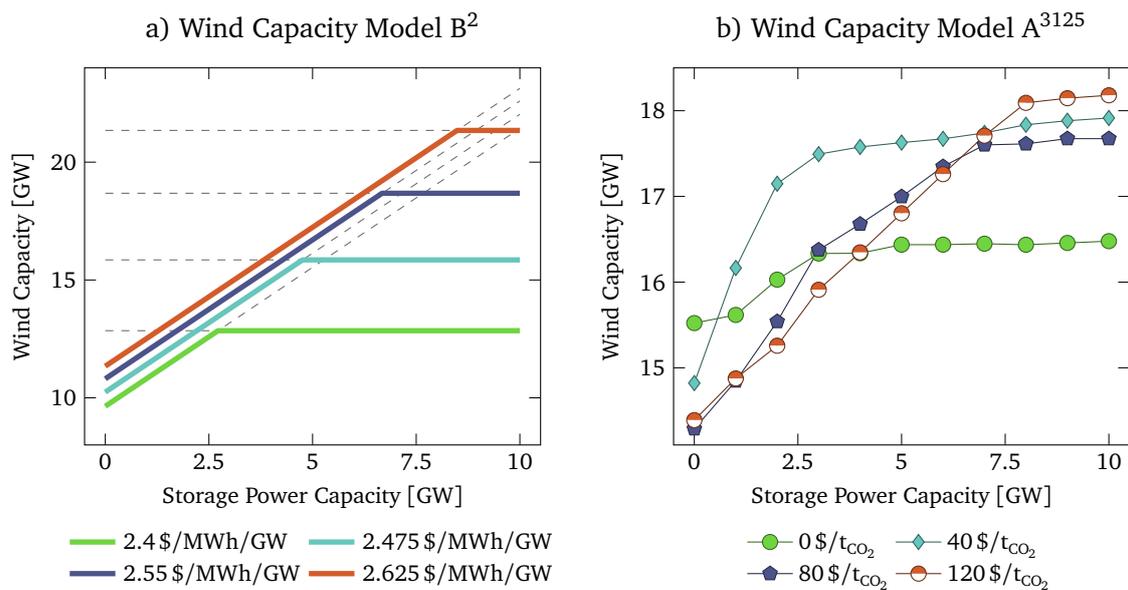


Figure 5.12

Dependence of the installed wind capacity on the available storage capacity in **(a)** the Model B² and **(b)** the Model A³¹²⁵.

Seasonal Contributions

In the two-hour model the resulting marginal costs are fully defined by the capital cost of the wind turbines. In the comprehensive model the value of the wind turbines is the sum of the value from energy transfer at various levels of marginal costs (in addition to the direct output). For example, while energy will be used to replace the output from

simple combustion turbines in summer, this is not the case in winter when the reduced demand limits the need for expensive peak power. This effectively prohibits a quantitative comparison of the two models in this regard.

An example for the qualitatively different impact of increasing storage capacity during different seasons is provided in figure 5.13 for the emission cost of $c_{\text{CO}_2} = 40 \text{ \$/t}$:

- The **total charging energy during the hours of wind power production** increases somewhat linearly before plateauing for very high storage capacity. While the behavior is qualitatively the same in March and August, the magnitude in March is much lower. This is a consequence of the reduced demand level and the less pronounced anti-correlation between wind power and load during this month.
- The **smaller electricity prices during the discharging in March** compared to August are the driver behind the difference shown in a). In general, a decrease of the electricity prices can be expected as the storage discharge power avoids the need for the most expensive electricity generation. The stable value in August is due to the storage's role as the price-setting technology: The NGCC generators are operating at full capacity during the peak hours of the month, which requires energy to be

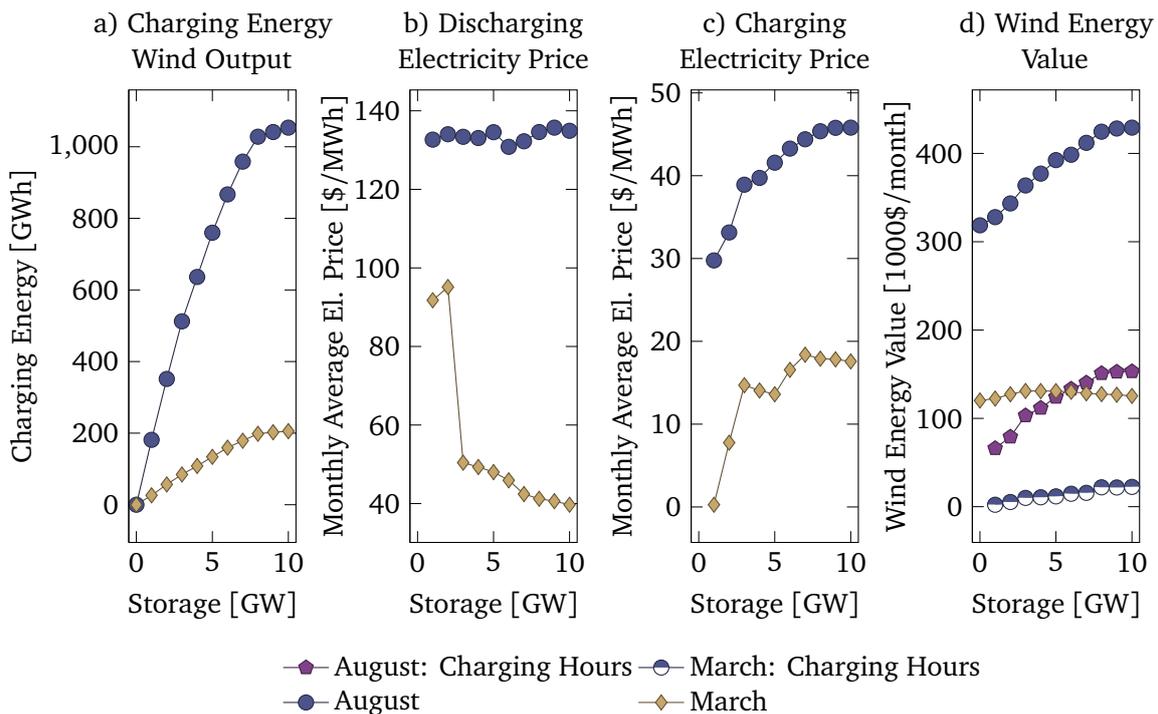


Figure 5.13

Seasonal difference in the value generation from wind power for $c_{\text{CO}_2} = 40 \text{ \$/t}$: **a)** The total charging energy during the hours of wind output increases roughly linearly during all seasons, followed by a saturation. **b)** The marginal values during the discharge are dominated by the peaker plants used during the respective seasons. In March the electricity generation from biomass power plants is entirely avoided for higher storage levels, causing a sudden drop at 3 GW of storage. **c)** The charging occurs at increasing price levels as the electricity demand during the corresponding hours rises. **d)** The value of the wind turbine output arises mainly in August; the increase can be attributed entirely to those hours where the charging takes place.

(expensively) transferred to provide the marginal unit (and to avoid the use of the even more expensive conventional natural gas plants). The drop in March between the 3 and 4 GW storage scenarios occurs as the power of the discharging entirely replaces the generation from NGCC plants during this month.

- c) The **electricity prices during the charging** rise as the higher storage charging power raises the demand during the hours of lowest effective load. The dominance of the biomass generator as a marginal technology in summer during those hours is reflected by the price levels in August, close to the variable cost of this type of power plant (34 \$/MWh).
- d) Finally, the **increasing value of the electricity generated from wind turbines** at higher storage levels justifies their capacity expansion. Most of this additional value arises in Summer (as shown by the comparison of the representative data for March and August) and—naturally—during those hours where the charging power is not equal to zero (illustrated by the nearly constant difference between the two corresponding curves in August). For high storage capacities the value of the electricity generated in March experiences a decrease, as the summer months drive the expansion and the high levels of wind power erode the marginal electricity prices in March.

Summary

More storage capacity in the system consistently favors the installation of wind turbines. The basic mechanism can be illustrated by a minimalistic 2-hour model: The storage-induced value increase of the wind power production arises indirectly through the higher marginal cost of electricity during the hour without wind output. While the qualitative agreement with the full model is given for some selected metrics, its interpretation is impeded by

- the discreteness of the supply curve of the conventional generators
- the pronounced monthly variation of the demand and the wind resources.

The high demand and electricity prices lead to an overwhelming dominance of the summer months' contributions to the storage-induced value of wind power, despite the lower capacity factors during this season.

5.6 OBSERVATION D: Replacement of Biomass Power Plant Output with Electricity from NGCC Plants

As shown in figure 5.7D an increase of the storage capacity from 1 to 3 GW at $c_{\text{CO}_2} = 80 \text{ \$}/t_{\text{CO}_2}$ induces a rise in the output from the combined cycle plants, which in turn causes a net increase of the system's total carbon emissions when compared to the zero-storage scenario.

Ultimately, the underlying mechanism is the reduction of the amount of biomass capacity added to the system due to the storage-induced increase of wind capacity: The maxima of the wind turbine output reduce the viability of base load-serving power plants in this specific case. This is less the case for the peaker plants, since scaling the the output from the wind turbines leads to much smaller absolute changes at their minima. As less biomass-power is added to the system the missing electricity during calms is provided by an increase of the production from NGCC plants.

This shows that the storage's role in terms of CO₂ emissions is somewhat threefold in these scenarios:

- It leads to **higher wind capacities providing clean power** which partly replaces the electricity from combined cycle plants, yet
- **indirectly causes the demise of the biomass plants** at the benefit of the electricity production from natural gas; and third,
- it **enables the transfer of clean electricity** to the maxima of the effective load, where it serves to replace the output from the gas-fueled power plants and to further mitigate the impact of the erosion of the clean base load power plants.

In the specific system configuration considered here the second effect is dominant.

In this context also the cost on carbon emissions has two competing effects: It favors the clean energy production from wind power causing the demise of the biomass plants, yet makes the latter more competitive. However, the strong promotion of the emission-free generators through this policy instrument leads to a consistent decrease of emissions for higher carbon costs, *ceteris paribus* (see figure 5.7D).

The importance of wind power is demonstrated by the analysis of an additional third scenario, called 1 GW-HIGH WIND. It is characterized by

- a) low storage power capacity of 1 GW, and
- b) the same wind and solar power capacity as in the 3 GW-storage scenario.

The relevant capacities and energies relative to the 3 GW-storage scenario are shown in figure 5.14. The optimal state of the 1 GW-HIGH WIND scenario has the exact same biomass capacity as the original system with 3 GW of storage (red arrow), which shows that the demise of this technology is a consequence of the increasing wind turbine capacity. At the same time the combined cycle plants and the combustion turbines compensate for the lack of energy discharged from, and the capacity of storage.

While the biomass capacity is thus unaffected by storage, the high storage capacity in the original scenario helps to mitigate the impact of the wind capacity. Since this possibility for mitigation is reduced in the 1 GW-HIGH WIND scenario, the *output* from nearly all generators is modified by the high wind capacity: In this case the lack of storage

- inhibits the use of the emission-free base-load plants (nuclear and biomass) for charging, thus causing a decrease in their output;

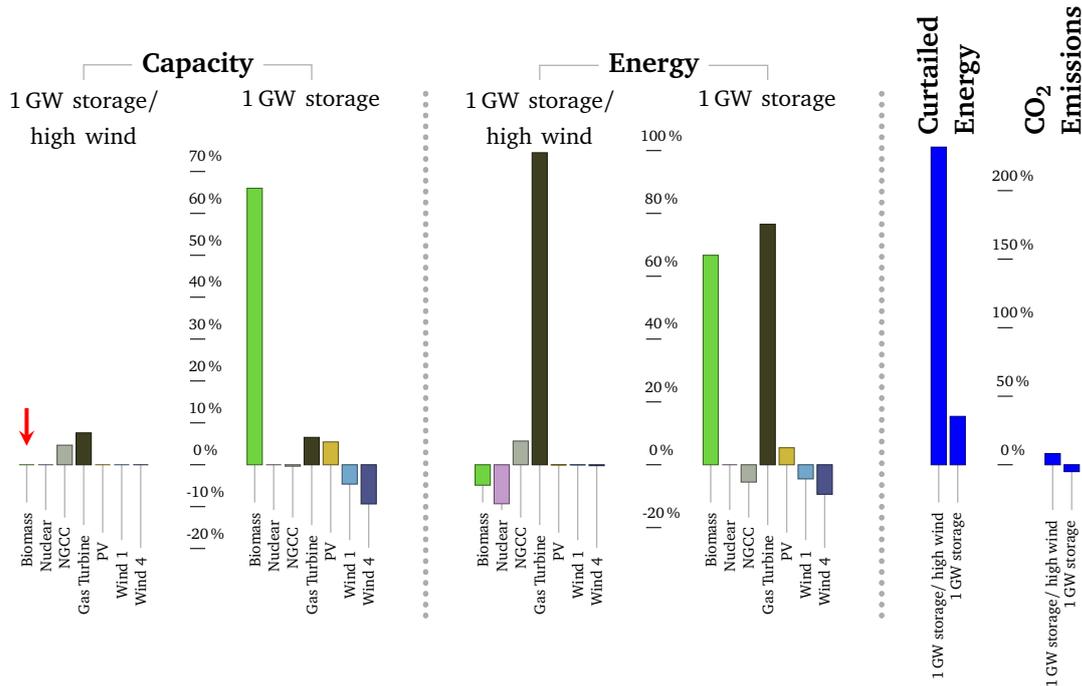


Figure 5.14

Relative changes of key variables with respect to the 3 GW scenario. In the HIGH WIND scenario the total variable generator capacity was set to the same level as the optimal amount in the 3 GW scenario. The observation that the biomass capacity (red arrow) is not affected by the presence of storage but by the presence of the higher variable generator capacity demonstrates that the replacement effect in this case is indirect: More storage leads to more wind capacity which leads to the replacement of biomass output.

- it causes higher curtailment rates; and
- raises the need for the generation from NGCC and conventional natural gas plants.

In total, this leads to even higher carbon emissions when compared to the original 3 GW-scenario. This comparison also illustrates once more that the storage directly benefits the base load plants, but that it indirectly erodes their economic performance.

Change of Intermittent Capacity and Storage

Increasing storage capacity in the system thus leads to a rise of wind power causing the erosion of the base-load regime where the expansion of the biomass capacity is viable, consequently making the NGCC plants a cheaper alternative. This is in contrast to today's power systems, where the ongoing expansion of variable cost capacity is often reported to take peaker plants into dire straits. In the system discussed here the specific combination of capital cost and wind resource makes wind power at location 4 very competitive, such that the impact of carbon emissions costs and storage capacity are limited to variations around this high wind penetration scenario. It is therefore instructive to consider the

cases where the total wind and solar capacity is limited to certain maximum values.

The plot 5.15a) shows the electricity production from the biomass and NGCC plants as the total intermittent generator capacity is ramped up from 0 to 30 GW. The near-linear replacement of NGCC output up to a wind capacity of 21 GW demonstrates this “merit-order effect”, which in Germany led to the demise of the gas-fueled generation capacity and the increasing production from coal plants under their (economic) must-run conditions [82].

Above this level of variable capacity the operating regime of the gas plants is expanded toward lower effective load levels, to the disadvantage of the biomass plants, leading to a partial and transient recovery of the NGCC plants. Storage (with capacity of 10 GW) causes this transition to occur within a shorter range of wind and solar capacity:

1. The onset is delayed as the storage allows to run the biomass power plants during the hours of peak wind power output. This increases the value of this technology to such an extent that the maximum possible capacity is installed up to a variable capacity of 21 GW.
2. The demise of the biomass power plant capacity with higher variable capacity is accelerated (see the data at 25.5 GW of variable capacity in figure 5.15a) as the storage causes the wind capacity to be more competitive compared to photovoltaics (within the constraint on the total variable capacity; see figure 5.15b) and c); compare the discussion in section 5.7).

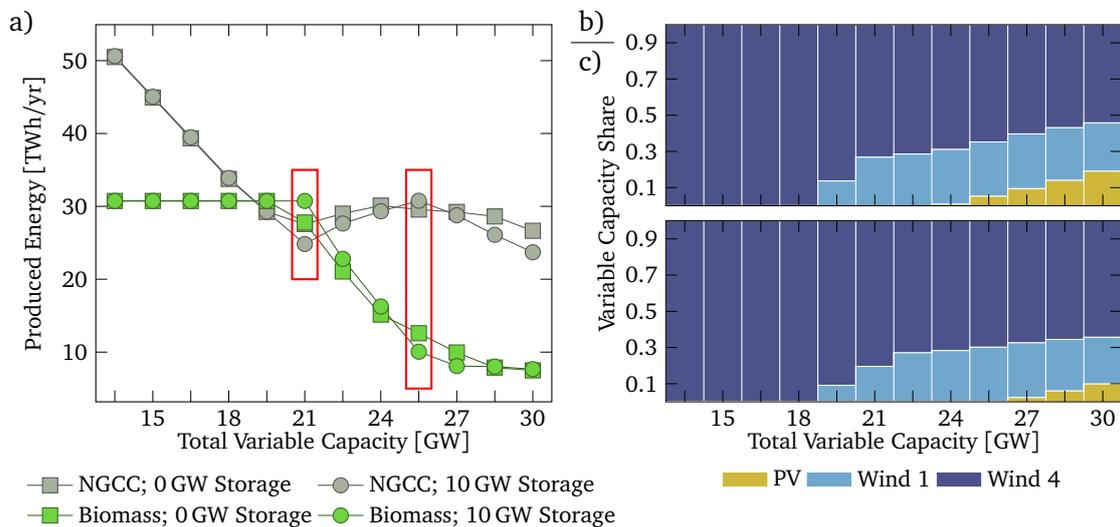


Figure 5.15

a) Energy produced from biomass and NGCC plants in dependence on the total capacity of variable electricity sources for two different levels of storage capacity. The base load power plants (biomass) are kept longer in the system when storage is present (left red rectangle); however, it is then replaced more quickly for increasing variable capacity (right rectangle). The variable generator portfolio composition is shown for the cases of zero storage capacity **(b)** and 10 GW of storage capacity **(c)**; wind power at location 4 is favored by the storage, which also causes the faster reduction of the biomass output in a).

In conclusion, similar to the discussion in the previous section, storage has two opposite effects during the transition from the erosion of peak load to the erosion of base load power plants, depending on the absolute level of variable capacity.

Summary

In this particular system higher storage capacity causes a shift of competitiveness from the biomass to the NGCC power plants, i.e. from base- to peak-load plants. This effect is indirect: Higher storage levels induce the installation of additional wind capacity, which in this case causes a disproportionate reduction of the capacity factor at the load level otherwise covered by biomass generator output. Thereby, the impact on the base load is a consequence of the specific penetration level of wind power in this scenario; lower wind capacity levels would impede the operation of the peaker plants. This again would be exacerbated by the storage output, which enables the increase of the capacity of the low-variable cost biomass generators.

Both the storage capacity constraint and the cost on carbon emissions thus have two competing effects:

- by increasing demand during wind peak hours and by raising the variable costs of electricity generation from fossil-fuels they increase the value of the output of both the variable and the biomass generators;
- by increasing the wind power capacity, the economic performance of the biomass power plants is deteriorated.

5.7 OBSERVATION E: Impact on Photovoltaics

The capacity factor and LCOE of photovoltaics are much less favorable compared to the properties of wind power at any of the four locations (see figure 5.2). Solar power therefore plays a minor role in the system's least-cost state, despite the relatively high correlation of its electricity production with the system load (see figure 5.4). The total installed photovoltaic capacity and energy production has been found to be affected by increasing volumes of installed storage capacity in various ways, depending on the price of the carbon emission allowances: While no impact is observed at 0 \$/t_{CO₂}, higher storage capacity undoes much of the PV capacity addition for 40 \$/t_{CO₂}. It is thus only for carbon prices of 80 \$/t or higher that the expansion of the PV capacity continues at higher storage levels before experiencing a small drop at very high storage power capacity.

Higher Competitiveness of PV at Zero Storage Capacity

While photovoltaics is perfectly non-competitive at zero carbon emission costs and the additional capacity in the 40 \$/t_{CO₂} scenario is reduced as the introduction of storage gives wind power a higher value, the two scenario sets with 80 \$/t_{CO₂} and 120 \$/t_{CO₂} see high

levels of PV capacity additions which remain largely unaffected by additional storage capacity. Before assessing the impact of storage on the viability of photovoltaics it is thus instructive to illustrate why the higher cost on carbon emissions favors this technology in the first place.

When accounting for all shadow prices, the net present value of all capacity additions is equal to zero in the cost-minimized system, which means that the marginal value of the output and the capacity is exactly equal the present value of the total (fixed and variable) marginal cost of the asset. In the absence of other binding constraints on the capacity or the output (such as the RPS), the total value of the produced electricity is solely dependent on the hourly shadow price of demand mc_t and the corresponding output $p_{r,t}$ of the respective generator. The value of the output from *newly* installed capacity $P_{new,r}$ is then simply the fraction $P_{new,r}/P_r$, as all instantaneously generated units of electricity have the same specific value. In the simpler case of the zero-variable cost generators, it must hold for the value V_r of all technologies r that

$$V_r = \sum_t mc_t \cdot p_{r,t} \cdot \frac{P_{new,r}}{P_r} = (c_{p,fc,on,r} crf + c_{p,fc,om,r}) \cdot P_{new,r} \quad (5.2)$$

with the capital recovery factor crf . The product $mc_t \cdot p_{r,t}$ suggests that the impact of the carbon cost on the temporal profile of the marginal cost of electricity changes the balance of wind and solar power. It is somewhat intuitive—given the dominant role of combined cycle gas plants to cover the peak load—that the cost on carbon amplifies the price peak during the daily load maxima, which coincides with the output from solar photovoltaics. A closer look at the data, however, reveals that both the wind (location 4) data and the hourly output from photovoltaics see a decrease in correlation with the marginal cost during most months of the year if the carbon cost is increased. In winter this is due to the lack of a pronounced afternoon peak (here the correlation with the wind power increases, but at very low marginal cost levels). In summer the marginal cost peak occurs in the evening at/after sunset. This also exacerbates the anti-correlation of wind and demand discussed in section 5.1. It must be stressed that this property is system-specific and might very well be the reverse if coal-fueled plants were being relied upon to provide the base-load, such that electricity would get disproportionately more expensive during the night.

It has been widely discussed in literature [83] that the marginal value of intermittent power sources can be disintegrated into

- a part A, solely dependent on the average capacity factor and the average marginal cost of electricity—this gives the **time-independent benefit** from using the zero-variable cost technology—and
- a part B, the covariance between the hourly capacity factor and the marginal cost; this expresses the **benefits from producing electricity when it is needed most**:

$$mv_i = 8760 \cdot \left(\underbrace{\langle mv_t \rangle_t \langle cf_{t,i} \rangle_t}_A + \underbrace{cov(cf_{t,i}, mv_t)}_B \right) \quad (5.3)$$

Figure 5.16 shows how the parts A and B contribute to the total marginal values of PV and wind turbines at location 4. While the higher cost on carbon modifies the profile

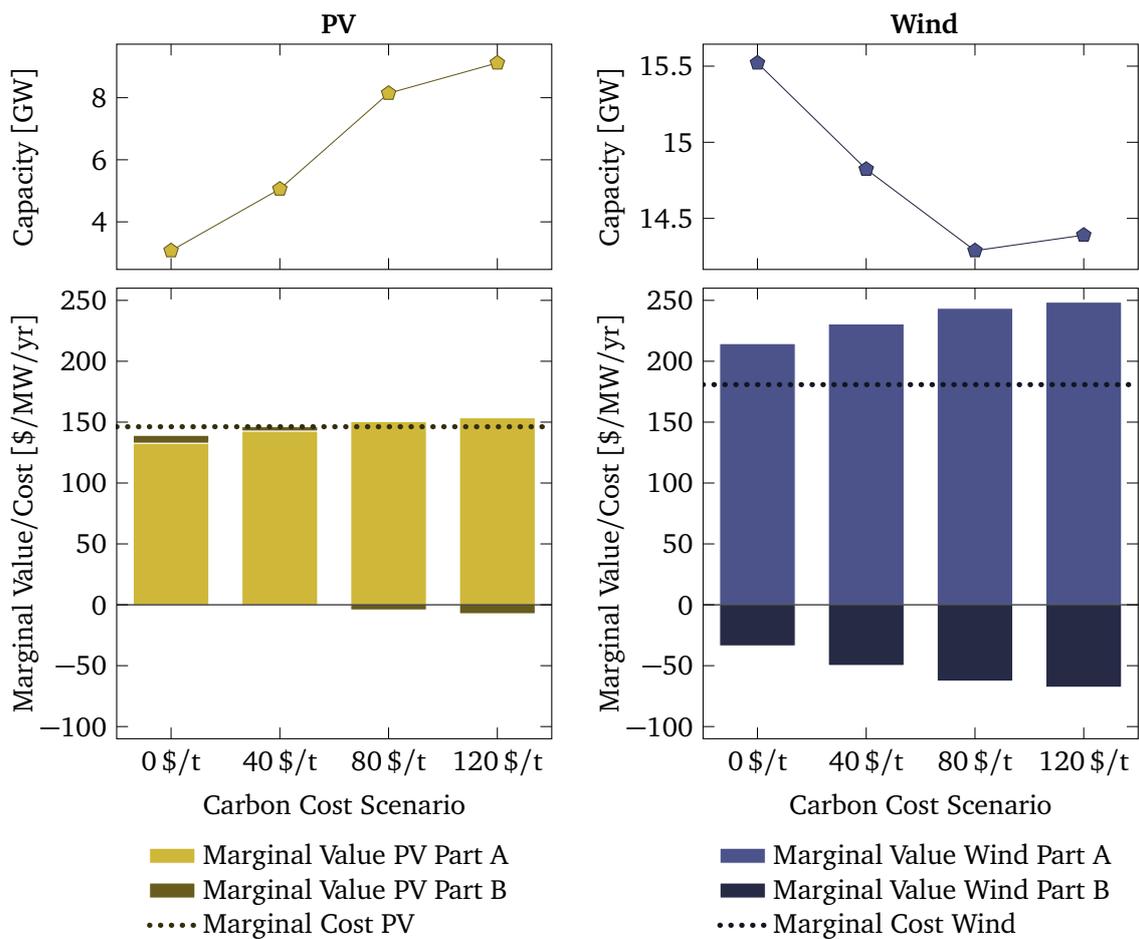


Figure 5.16

Contribution from bulk (part A) and demand-matched electricity production (part B) to the total marginal value of wind and PV capacity. While the high capacity factor of wind power makes this technology very competitive, this advantage is partly compensated by the worse fit with the marginal cost at higher costs on carbon emissions, which manifests itself in lower capacity additions.

of the electricity price in a way that causes a decrease in the correlation coefficient, the covariance of the two technologies' outputs and the marginal cost strongly favors photovoltaics over wind turbines: Wind power sees the higher contribution from part A in equation 5.3 being eroded by the decreasing matching of its output with demand, for photovoltaics the contribution from the part B is much less, which allows its marginal value to rise above the specific fixed cost for $c_{CO_2} \geq 40 \text{ \$/t}_{CO_2}$. At the same time the higher capacity factor of wind power compensates for the lower quality of the matching with demand and allows this technology to experience (reduced) capacity additions also for higher costs on carbon emissions.

Impact of Storage on PV and Wind Power in High-Carbon Cost Scenarios

The increase of storage in the system has the potential to raise the marginal value of both solar and wind power and thereby cause a higher capacity of these technologies to be part of the system's least cost state. This potential is limited by the demand during the hours to which the energy is transferred, which effectively leads to a competition of solar and wind power for the limited demand resource. Very similar to the discussion of equation 5.3 the two primary properties which affect the final balance of the two power sources are given by:

- a) the quality of the match of the electricity sources' temporal output profile with the system demand;
- b) the total capacity factor of each technology.

The analysis of the simple 3-hour Model B⁵ (see section 3.3) allows to isolate the relevant effects and interdependencies (see figure 5.17): Similar to the increase of the emissions costs in the Model A³¹²⁵ an increase of the slope of the conventional generators' supply curve causes a qualitative change of the photovoltaic capacity depending on the storage capacity. For low marginal costs any increase of the storage capacity causes the demise of photovoltaics, while higher running costs of the conventional generators allow this technology to gain a competitive edge before losing its value. This is in qualitative agreement with the observations in figure 5.7E.

It should be noted that setting the total capacity factor of photovoltaics equal to the one of wind power inverts the qualitative dependence of the capacities of these two technologies on the storage capacity, everything else equal. In this case the better match of the solar output with the intermediate demand level during time slot 2 provides the pivotal competitive advantage. This corroborates the qualitative symmetry of the two properties mentioned above.

The discussion of the storage-dependent marginal cost level during the time slot 3 is best suited to assess the underlying mechanism of this replacement. As long as wind and solar power are viable components of the system the marginal costs during the time slots 1 and 2 are constant and correspond to⁵:

- *Slot 1*: the cost of covering a marginal unit of demand in slot 1 by increasing the wind turbine capacity, which allows to decrease the solar capacity in slot 2: $mc_1 = c_{cap,w} \cdot cf_{1,w}^{-1} - c_{PV} \cdot cf_{2,w} \cdot cf_{2,PV}^{-1}$;
- *Slot 2*: the cost of covering a marginal unit of demand by increasing the photovoltaic capacity: $mc_2 = c_{PV} \cdot cf_{2,PV}^{-1}$.

Since the output from both wind and solar is zero during time slot 3, the electricity price during this time is determined by the linear supply curve of electricity from the conventional generators and the availability of power output from storage. Figure 5.17a) shows this dependence; four qualitatively different ranges of the marginal cost levels can be identified (corresponding to the labels in the figure):

⁵This also requires the storage round-trip efficiency to be low enough not to make the transfer of energy from slot 1 to slot 2 a viable option.

- A For low storage capacity the difference in marginal costs between the three time slots is sufficiently large to make the simultaneous installation of both wind and solar power viable. For each 1 GW increase of storage capacity this leads to the generation of 1 additional gigawatt of power during both time slots 1 and 2 (due to the storage roundtrip efficiency of $\eta = 0.5$), causing the decline of the marginal cost during the slot 3 at a rate equal to dmc_{CG}/dp , the slope of the conventional generator supply curve.
- B This rapid decline ends when the discharging power is high enough to lower the marginal cost in slot 3 to the level $mc_2\eta^{-1}$. In this case the transfer from slot 2 to slot 3 is not an option any longer. The increase of storage power capacity induces the continuation of wind power capacity build-out. However, any additional energy transfer to the time slot 3 requires the complete replacement of the charging during the time slot 2. This causes the system to remain unchanged by additional storage capacity until the storage level is high enough to allow the electricity production during the time slot 1 to cover the total volume of transferred energy. As this build-out of wind power capacity also causes the generation of electricity during the time slot 2, the PV capacity is increasingly replaced.
- C Once the charging during time slot 1 is the only supply to the energy storage, the marginal cost during the time slot 3 continues its decrease at a rate $0.5 dmc_{CG}/dp$ until it reaches the value $\eta^{-1}mc_1$.

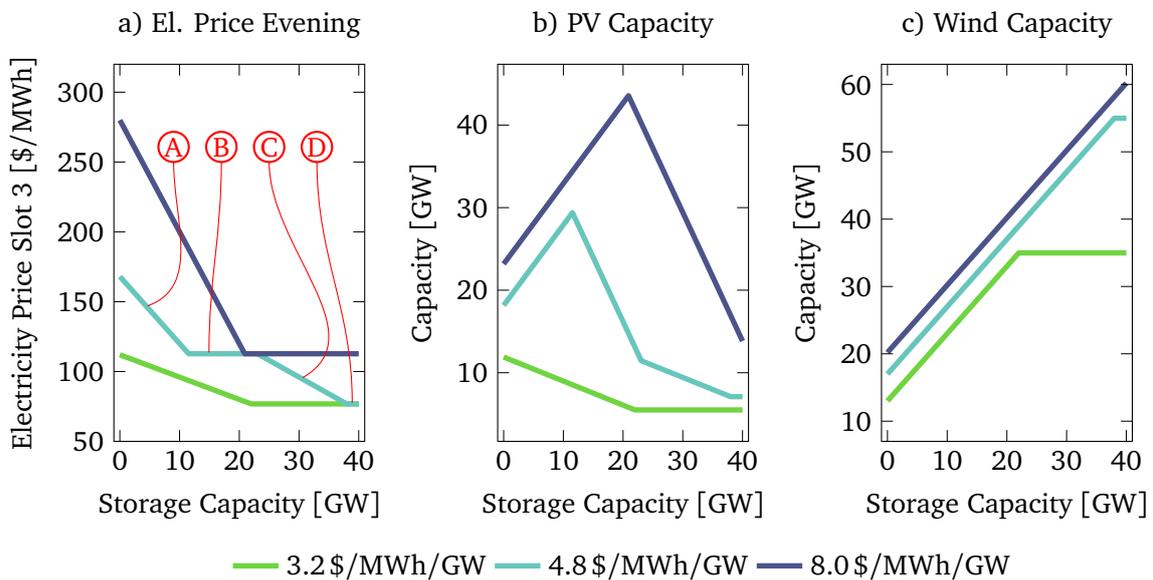


Figure 5.17

Changes in the 3-hour model with increasing storage capacity for different slopes of the conventional generator supply curve: **a)** The marginal cost during the time slot 3 (discharge) shows 2 distinct plateaus, depending on which of the other hours/variable technologies provides the marginal charging energy. **b)** The photovoltaic capacity as a function of the storage capacity; while small amounts of storage lead to high marginal values from additional PV capacity, the higher capacity factor of wind power ultimately leads to the replacement of photovoltaics. **c)** The installed wind capacity experiences a continuous increase until the benefit of transferring a marginal unit of energy to the time slot 3 is equal to the capital cost of this technology.

- D At this level no energy transfer is possible for the given round-trip efficiency η , which implies that the system will not be affected by additional storage capacity.

The resulting storage-dependence of the PV capacity additions in figure 5.17 serves to explain the corresponding observations in figure 5.7E:

- The immediate replacement at $40\$/t_{CO_2}$ indicates that the transfer of additional electricity from photovoltaics is not worth the capital cost in this scenario. While large amounts are added due to the high marginal value at this carbon price, the storage-induced rise of wind power leads to the replacement of PV energy and the avoidance of PV capacity additions.
- For the two scenarios with higher carbon cost both wind and solar power are favored by small storage capacities. This proceeds until this trend is reversed for photovoltaics. The fact that the amplitude of these changes is very small can be attributed to the disproportionately higher value of solar power due to the cost on carbon emissions. Furthermore, similar to the discussion on wind power, the seasonal diversity of the contributions to the values of the variable technologies is a hindrance to the quantitative interpretation of the exact mechanisms.

Summary

The impact of the storage and carbon costs on the viability of photovoltaics has been found to be diverse and primarily driven by the competition with wind power and the changing correlation of its output with the system's electricity price profile. Wind and solar power indirectly compete for the same demand during the hours of the storage discharge. Depending on the demand-matching and the capacity factor the more competitive of those resources will finally replace the other one, after both wind and solar power benefit from small volumes of storage capacity.

5.8 Limitations

This study aims at the identification of qualitative mechanisms and their potential volumes in a stylized power system. While this reduces the need for accuracy in the representation of the system, several limitations must be borne in mind, which could have an impact on the applicability of the model in its current form and thus potentially call for its expansion.

- The **limitation to a single year of operation** leads to the implicit assumption that all operational parameters (fuel prices, cost on carbon emissions, RPS targets etc.) remain constant throughout the lifetime of all assets. However, this reduced approach allows for a much more comprehensive analysis of the mechanisms underlying the differences between various scenarios. In contrast, a full fledged multi-period model is expected to cause much larger amplitudes in the investment dynamics of the model, primarily due to the changing fuel and capital costs, and the limited life

times of the assets.

To optimize the composition of the system the use of equivalent annual capital costs is indeed not fully valid as long as generator capacity is included in the system *a priori*: Since this approach is based on the assumption that assets are replaced with the same assets at the end of their lifetime, not putting a cost on any of the capital leads to distortions and strongly favors the incumbent technology. Because of this, a more rigorous approach can be expected to enhance the impact of storage capacity.

- The specific assumptions made on the **technical and economic properties of the storage types** are expected to have a significant impact on the overall least-cost state of the system. In the cases presented here, compressed air energy storage was the most viable among those technologies. This is mainly due to the competitive per-power capital cost and the negligible per-energy cost. However, the low round-trip efficiency η of this technology limits its use to situations where the electricity prices during the charging mc_{ch} and the discharging mc_{dc} are sufficiently different, i.e. $mc_{\text{ch}} < \eta mc_{\text{dc}}$. In a system evolving over time other storage technologies with much higher round-trip efficiency (such as lithium-ion batteries) might gain a competitive edge as their capital cost decreases, having a much higher impact on the system's operation.
- The strongly limited vertical topological resolution of the model, i.e. the **omission of grid levels** puts an emphasis on large centralized resources. This forms a severe limitation in the representation of a power system such as the one in California, where an increasing emphasis is being put on the generation of electricity from distributed resources [33]. Introducing an additional level representing the distribution grid would allow to capture the systemic benefits of distributed generation and put a higher value on solar photovoltaics.
- The **aggregation of power plants by technology**, represented by a single set of parameters and decision variables, neglects the technical and economic limitations of the units' operation. While simplified techniques have been devised to capture technical limitations and costs of the startup-cycles of these aggregate generators [84], the implementation of these techniques has been found not to be a computationally feasible strategy within the framework of this study. This is mainly due to the optimization of the operation of several storage technologies, which is highly demanding by itself. In general the reduction of the flexibility of the generators' generation can be expected to put a higher value on energy storage and a lower value on inflexible base-load capacity.
- With grid-connected storage expected to obtain most of its value from a participation in **ancillary markets** [13, 42], the omission of these markets forms a strong limitation. Generators able to adapt their output quickly to external commands can be expected to become less relevant if this service is provided by storage solutions, which would make the peak-load providing plants relatively less competitive.
- **Demand response and energy efficiency** are not explicitly considered within the framework of this stylized model. This is in contrast to the assumptions of the *California 2030 Low Carbon Grid Study*, where demand response for peak reduction of up to 7.3 GW and peak demand reduction through energy efficiency measures of up to 13.3 GW were found to be viable components of a cost-effective system state in 2030 [38]. This suggests that they would constitute important expansions of the

model presented here.

- California is rather well-connected to the other states of the WECC and covers a significant share of its electricity demand through imports [85]. This is the also the reason why the WECC area is often modeled as one entity, as in some of the studies described above. A **single-node representation** was chosen for this study to keep the calculations within the reach of the available computational resources and to facilitate the interpretation of the results. As long as the focus of the study lies on qualitative mechanisms, a topological expansion to several nodes is not an urgent matter.

Chapter 6

Conclusion

The impact of large scale energy storage on power systems have been found to be subtle, yet diverse, and to feature a strong dependence on the temporal structure of the marginal electricity price, modulated by the cost on carbon emissions in this particular example. However, in many cases the subtlety of these findings are a consequence of the specific composition of the stylized system considered here, and could therefore be much stronger in alternative configurations (e.g. when choosing a different geographic entity's power system as a starting point). An illustrative overview of the direct and indirect impacts of storage on the system is shown in figure 6.1. In short, the following conclusions can be drawn:

- Storage causes the **direct optimization of the operation of base load power plants**, allowing those assets to produce more electricity per unit of installed capacity. This is driven by an increase of the value of electricity due to the charging during the hours of lowest effective load. In the system considered here it is primarily the

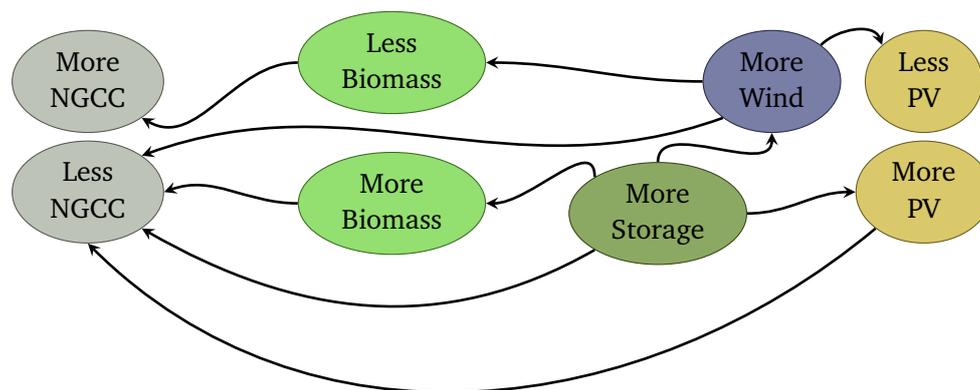


Figure 6.1

Direct and indirect impacts of increasing storage capacity on the stylized power system considered in this study. Various technologies are supported by increasing the value of their output and capacity. Wind power plays a pivotal role in the indirect replacement of other technologies.

biomass-fueled power plants which experience the largest support in this respect. Since the stored energy is finally used to replace the electricity production from gas-fueled plants, this effect is environmentally beneficial if carbon emissions are chosen as the sole metric. However, it must be borne in mind that in a different system configuration—if the base load were covered by coal power plants—the result would be the increase of the production from coal power plants at the expense of cleaner gas-fueled peaker plants.

- The most dominant effect of higher volumes of storage capacity is the **increase of the value of wind power**, which leads to larger capacities to be part of the system's least-cost state. In the same way as above, this is due to an increase of demand and electricity prices during the hours of highest wind power production. It is mainly these rises in capacity that drive other (indirect) changes in the system: Most interestingly, under some circumstances the increase in wind power erodes the value of electricity produced from biomass power plants to a sufficiently large extent to compensate the value increase from the cost on carbon emissions. As a result, the system sees less biomass capacity additions and the increase of electricity output from natural gas combined cycle plants. In this case the addition of certain amounts of storage capacity has the adverse effect of partly neutralizing the emission-mitigating action of the cost of carbon emissions. Storage then has essentially three effects, the third one overcompensating the other two:
 - a) storage enables the transfer of clean wind and solar electricity to the demand peaks where it avoids the gas-fueled power production;
 - b) it enables the cost-effective transfer of biomass-generated electricity to the hours of highest effective demand, again replacing the electricity production from gas;
 - c) at the same time it compromises the value of the biomass plant capacity by providing support to wind power.

While the increase of storage capacity is not the only way to support wind power up to the point where it causes the demise of the base load power plants, this example provides an illustration of the multiple, possibly competing drivers which result from increasing volumes of storage capacity in a power system.

- Finally, **storage benefits both wind and solar power**; small volumes of storage capacity result in higher capacities of both these technologies as the value of their variable output increases. However, once the system's marginal cost variations are sufficiently reduced, even higher capacities of storage lead to the demise of the less competitive of these technologies. Thereby, relative competitiveness is a result of both the total capacity factor and the matching of the variable output with the temporal marginal cost profile.

6.1 Future Work

The mechanisms presented above remain largely system-specific and can be expected to either change in amplitude or in type if the system is modified or expanded. Because of this, a continuation of this project could proceed along several main strands (or combinations thereof), all of which are based on linear modeling:

1. The **comparison to other power systems** with qualitatively different compositions of the generator fleet would allow to reveal conceptual differences, amplitudes of effects and possibly additional mechanisms, while maintaining the original stylized approach. An obvious choice for this comparison would be Germany, where most of the base load is covered by coal-fired power plants. Potentially higher costs on carbon emissions make the base load more expensive in that case, which would lead to an even higher value of wind capacity. At the same time higher storage capacities would provide real economic incentives to ramp up the production from coal-fired power plants in order to avoid the electricity generation from more expensive peaker plants.
2. While a temporally more complete model with **multiple investment periods and limited asset lifetimes** has been implemented within the framework of this study it was finally not used, mainly due to the associated complications when aiming at a full description of the observed effects. However, in a second step a model like this would allow to overcome many of the limitations described in section 5.8, in particular the limited competitiveness of other storage technologies and the overly strong economic performance of the initially installed capacity.
3. In contrast to the points above, another option consists in the more realistic representation of the system. Since a large part of the grid-connected storage is envisioned to be installed at the distribution level, it would be beneficial to **include various grid levels**, i.e. one or several representative distribution systems together with the transmission system; this would allow to capture additional benefits of storage (and distributed generation) such as avoided transmission losses and other system benefits associated with self-consumption.
4. The introduction of **ancillary markets** into the model used for this study is expected to cause the value of storage assets to increase at the expense of the peaker plants. A possible approach could be based on the methods used by Byrne *et al.* [42] and Cutter *et al.* [13], modified to fit a model with endogenous prices for electric energy and ancillary services.
5. Finally, to assess the effect of storage in an actual system, a shift to a **topologically more complete representation** would be desirable, including all nodes, interconnections and transmission constraints, possibly complemented by ancillary markets and several grid levels; this would allow for clear policy recommendations. Thereby, the development of such a complete approach would greatly benefit from studies as presented in this report, which assess the relevant time-scales (thus defining the possible simplifications) and allow for a complete understanding of the relevant effects, thus facilitating the interpretation of a comprehensive model.

Appendices

Appendix A

Technical and Economic Properties of Storage Technologies

I

A.1 Properties of electrochemical storage types

Type	Reference	ON Capital power cost [\$/kW]	ON Capital energy cost [\$/kWh]	ON Capital cost [\$/kW]	Fixed O&M cost per power [\$/kW/yr]	Round trip efficiency	Energy loss	Variable O&M \$/Mwh	Calendar life time	Depth of discharge	Rated power	E2P [h]	Markets/ Applications
LiTi	[12]	703\$ (2008), 411\$ (2030)	318\$ (2008), 192\$ (2030)	1021\$/ 3247\$ (2008), 1975\$/ 8335\$ (2008), 603\$/ 1179\$ (2030), 1947\$/ 5019\$ (2030)	12.3\$ (unc.)	0.81 (2008)	8.33e-5/h (2008)	0\$ (2008)	15 (unc.)	-	-	f1/f4/f8/f24	all
Li-Ion	[86, pp.xxiii]	-	-	1085–1550\$	-	0.87–0.92	-	-	-	-	1-100	f0.25–1	all
Li-Ion	[86, pp.xxiii]	-	-	1800–4100\$	-	0.9–0.94	-	-	-	-	1–10	f2–4	T&D Grid Supp.
Li-Ion	[87, pp.20]	-	-	4000–5000\$	-	0.9 (DC)	0.005 /wk [88, pp.292]	-	15	-	5	f0.25–4	all

Li-Ion	[89, pp.v]	305 (2011), 200 (2020)	1000 (2011), 510 (2020)	1305\$/ 4305\$/ 8305\$/ 24305\$/ (2011), 710\$/ 2240\$/ 4280\$/ 12440\$ (2020)	5	0.8	-	7	-	-	-	f1/f4/ f8/f24	-
“Batteries” (NiCd)	[90]	270– 530\$	330– 660\$	600–1190\$ 1590–3170\$ 2910–5810\$ 8190–16370\$	-	0.6–0.7	5– 20%/mth	-	N/A	-	-	f1/f4/ f8/f24	-
NaS	[86, pp.xxiii]	-	-	3100 – 3300\$	-	0.75	-	-	-	-	50	f6	all/no prim.
NaS	[86, pp.xxiii]	-	-	3200–4000\$	-	0.75	-	-	-	-	1	f7.2	T&D Grid Supp.
NaS	[87, pp.20]	-	-	1850–2150\$	-	0.8-0.85 (DC)	-	-	15	-	35	f8	all
“Batteries” (NaS)	[90]	270– 530\$	330– 660\$	600–1190\$ 1590–3170\$ 2910–5810\$ 8190–16370\$	-	0.6–0.7	0%/mth	-	N/A	-	-	f1/f4/ f8/f24	-
NaS	[88, pp.264]	-	-	3100–3300\$	-	0.75	-	-	-	-	50	f6	Bulk storage
NaS	[88, pp.264]	-	-	3200–4000\$	-	0.75	-	-	-	-	1	f7.2	T&D support
NaS	[88, pp.264]	-	-	3200–4000\$	-	0.75	-	-	-	-	1	f7.2	Comm./Indust.
NaS	[89, pp.v]	305 (2011), 200 (2020)	415 (2011), 290 (2020)	720\$/ 1965\$/ 3625\$/ 10265\$(2011), 490\$/1360\$/2520\$/7160\$ (2020)	5	0.78	-	7	-	-	-	f1/f4/ f8/f24	-
Adv. Pb-Acid	[86, pp.xxiii]	-	-	1700– 1900/2700\$	-	0.85–0.9	-	-	-	-	50/100	f4/f4	all/no prim.
Adv. Pb-Acid	[86, pp.xxiii]	-	-	950–1590\$	-	0.75–0.9	-	-	-	-	1-100	f0.25–1	all
Adv. Pb-Acid	[86, pp.xxiii]	-	-	2000–4600\$	-	0.75–0.9	-	-	-	-	1-12	f3.2–4	T&D Grid Supp.
Pb-Acid	[87, pp.20]	-	-	1740–2580\$	-	0.7-0.75 (AC)	-	-	4–8	-	3–20	fsec-4	all
“Batteries” (Pb-Ac.)	[90]	270– 530\$	330– 660\$	600–1190\$ 1590–3170\$ 2910–5810\$ 8190–16370\$	-	0.6–0.7	2– 5%/mth	-	N/A	-	-	f1/f4/ f8/f24	-
Pb-Acid	[88, pp.213]	-	-	1800\$	-	0.85	-	-	-	-	50	f4	Bulk/renewables
Pb-Acid	[88, pp.213]	-	-	950–1590\$	-	0.75–0.9	-	-	-	-	1–100	f0.25–1	Frequency reg.
Pb-Acid	[88, pp.213]	-	-	2000–4600\$	-	0.75–0.9	-	-	-	-	1–12	f3.2–4	T&D support
Pb-Acid	[88, pp.213]	-	-	2800–4600\$	-	0.75–0.9	-	-	-	-	0.2–1	f4–10	Comm./Indust.
Pb-Acid	[88, pp.213]	-	-	1600–3725\$	-	0.85–0.9	-	-	-	-	0.025– 0.05	f2–5	Distributed app.
Pb-Acid	[88, pp.213]	-	-	4520–5600\$	-	0.85–0.9	-	-	-	-	0.005	f4	Residential

ZEBRA	[87, pp.20]	-	-	1500–2000\$	-	0.93	-	-	N/A	-	10	f8	-
V Redox	[86, pp.xxiii]	-	-	3100–3700\$	-	0.65–0.75	-	-	-	-	50	f5	all/no prim.
V Redox	[86, pp.xxiii]	-	-	3000–3310\$	-	0.65–0.70	-	-	-	-	1–10	f4	T&D Grid Supp.
V Redox	[87, pp.20]	-	-	7000–8200\$	-	0.63–0.68	-	-	10	-	4	f4–8	all
						(AC)							
Zn/Br Redox	[86, pp.xxiii]	-	-	1450–1750\$	-	0.6	-	-	-	1.0[91]	50	f5	all/no prim.
Zn/Br Redox	[86, pp.xxiii]	-	-	1670–2015\$	-	0.6–0.65	-	-	-	1.0[91]	1–10	f5	T&D Grid Supp.
Zn/Br Redox	[87, pp.20]	-	-	5100–5600\$	-	0.6–0.7	-	-	20	-	2	f2–4	all
						(AC)							
Fe/Cr Redox	[86, pp.xxiii]	-	-	1800–1900\$	-	0.75	-	-	-	-	50	f5	all/no prim.
Fe/Cr Redox	[86, pp.xxiii]	-	-	1200–1600\$	-	0.75	-	-	-	-	1	f4	T&D Grid Supp.
Fe/Cr Redox ¹	[87, pp.20]	-	-	2000–2500\$	-	0.5–0.65	-	-	20	-	10	f2–4	all
Zn/air Redox	[86, pp.xxiii]	-	-	1440–1700\$	-	0.75	-	-	-	-	50	f5	all/no prim.
Zn/air Redox	[86, pp.xxiii]	-	-	1750–1900 \$	-	0.75	-	-	-	-	1	f5.4	T&D Grid Supp.
Zn/air Redox ²	[87, pp.20]	-	-	3000–5000\$	-	0.4–0.6	-	20	-	-	10	f3–4	all
“Flow batt.”	[90]	1100– 4500\$ ³	110– 320\$ ⁴	1210–4820\$ 1540–5780\$ 1980–7060\$ 3740–12180\$	-	0.6–0.7	0.0	-	N/A	-	10	f1/f4/ f8/f24	-
“Redox Flow Batt.”	[89, pp.v]	1416 (2011), 975 (2020)	215 (2011), 131 (2020)	1631\$/ 2276\$/ 3136\$/ 6576\$ (2011), 1106\$/ 1499\$/ 2023\$/ 4119\$ (2020)	41.5 (2011), 7 (2020)	0.75	-	1	-	-	-	f1/f4/ f8/f24	-

Table A.1

Properties of electrochemical storage systems

¹Rather experimental²Rather experimental³Low prices: “future”⁴Low prices: “future”

A.2 Properties of non-electrochemical storage types

Λ1

Type	Reference	ON Capital power cost [1/kW]	ON Capital energy cost [1/kWh]	ON Capital cost [1/kW]	Fixed O&M [\$/kW/yr]	Round trip efficiency	Energy loss	Variable O&M \$/MWh	Calendar life time	Depth of discharge	Power [MW] (if E2P fixed)	E2P [h]	Markets
A-CAES	[88]	1000€ (2013)	40-80€ (2013)	-	-	0.7-0.8	0.005-0.01/d	-	>25	0.35-0.5	-	1-10	all/no prim.
D-CAES	[88]	350-450€	1-30€	-	-	0.42-0.54	-	-	>40	0.35-0.5	-	1-10	-
D-CAES 20h	[86, pp.xxiii]	-	-	1250\$	-	-	-	-	-	-	135	f20	-
D-CAES 8h	[86, pp.xxiii]	-	-	1000\$	-	-	-	-	-	-	135	f8	-
CAES	[87, pp.20]	-	-	600-750\$	-	54-88	-	-	35	-	15-400	f2-24	-
CAES abv. grd.	[86, pp.xxiii]	-	-	1950-2150	-	-	-	-	-	-	50	f5	T&D Grid Supp.
CAES	[89, pp.v]	1000 (2011), 850 (2020)	3	1003\$/ 1012\$/ 1024\$/ 1072\$ (2011), 853\$/ 862\$/ 874\$/ 922\$ (2020)	7	0.5	-	3	-	-	-	f1/f4/ f8/f24	-
Flywheel	[88]	300€ (2013)	1000€ (2013)	-	-	0.8-0.95	0.05-0.15/h	-	15	0.75	-	< 0.25	all
Flywheel	[87, pp.20]	-	-	3695-4313\$	-	0.95	-	-	20	-	2	fsec-0.25	-
Flywheel	[86, pp.xxiii]	-	-	1950-2200	-	0.85-0.87	-	-	-	-	20	f0.25	all
Flywheel	[89, pp.v]	1362 (2011), 660 (2020)	148 (2011), 115 (2020)	1399\$ (2011), 689\$ (2020)	18	0.85	-	1	-	-	-	f0.25	-
P-Hydro	[88]	500-1000€	5-20€	-	-	0.75-0.82	5e-5 - 2e-4/d	-	80	0.8-1	-	1-10	all/no prim.
P-Hydro	[87, pp.20]	-	-	2700-3300\$	-	0.87	-	-	30	-	250	f12	-
P-Hydro	[89, pp.v]	1750 (2011), 1890 (2020)	10	1760\$/ 1790\$/ 1830\$/ 1990\$ (2011), 1900\$/ 1930\$/ 1970\$/ 2130\$ (2020)	4.6	0.81	-	4	-	-	-	f1/f4/ f8/f24	-
SMES	[87, pp.20]	-	-	380-490\$	-	0.9	-	-	20	-	1-3	fsec	Primary

SMES	[87, pp.20]	-	-	700–2000\$	-	0.9	-	-	20	-	100–200	fmin–10	-
Ultra-cap.	[87, pp.20]	-	-	1500–2500\$	-	0.9	-	-	20	-	10	fsec	-

Table A.2
Properties of non-electrochemical storage systems

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Appendix B

Technical Model Documentation

Asset Sets	
Dispatchable Generators	$g \in \{\text{Geothermal, Hydropower, Nuclear, Coal, Biomass, NGCC, Combustion Turbine}\}$
Variable Generators	$i \in \{\text{Photovoltaics, Concentrating Solar Power, Wind 1, Wind 2, Wind 3, Wind 4}\}$
Storage	$s \in \{\text{Lithium-Ion, Sodium Sulfur, Lead Acid, Redox Flow, Compressed Air, Flywheel, Pumped Hydro}\}$
Objective Function	
Objective function: The sum of all technologies' variable and fixed costs	$C_{\text{sys}} = \sum_g (C_{\text{vc,tot,g}} + C_{\text{fc,tot,g}}) + \sum_s (C_{\text{vc,tot,s}} + C_{\text{fc,tot,s}}) + \sum_i C_{\text{fc,tot,i}}$
Cost Calculations	
The total fixed costs $C_{\text{fc,tot,r}}$ are calculated as the sum of the capital costs $C_{\text{fc,on,r}}$ and the fixed O&M costs $C_{\text{fc,om,r}}$.	$C_{\text{fc,tot,r}} = (C_{\text{fc,on,r}} + C_{\text{fc,om,r}})$ with $r \in \{i, g, s\}$
The capital costs are the product of the capacity additions $P_{\text{new,r}}$, the specific capital costs $c_{\text{p,fc,on,r}}$ and the capital recovery factor crf .	$C_{\text{fc,on,r}} = c_{\text{p,fc,on,r}} P_{\text{new,r}} \cdot crf$ with $r \in \{i, g\}$
For storage technologies , the total capital costs are the sum of the cost of power and energy capacity additions, $P_{\text{new,s}}$ and $E_{\text{new,s}}$.	$C_{\text{fc,on,s}} = (c_{\text{p,fc,on,s}} P_{\text{new,s}} + c_{\text{e,fc,on,s}} E_{\text{new,s}}) \cdot crf$
Fixed O&M costs are obtained from the total installed capacity P_r and the specific O&M costs $c_{\text{p,fc,om,r}}$.	$C_{\text{fc,om,r}} = c_{\text{p,fc,om,r}} P_r$ with $r \in \{i, g, s\}$
Variable costs: The sum of all costs to produce/discharge the electric energy $d_t P_{r,t}$ at a specific cost $c_{\text{vc,r}}$.	$C_{\text{vc,r}} = \sum_t c_{\text{vc,r}} P_{r,t} d_t$ with $r \in \{g, s\}$
Specific variable costs: The variable O&M costs; plus the fuel and emission costs (for $r = g$).	$c_{\text{vc,r}} = c_{\text{vc,om,r}} + \delta_{r,g} (c_{\text{vc,fuel,r}} + c_{\text{vc,carb,r}}) / \eta_r$ with $r \in \{g, s\}$
Demand Constraints	
Demand: The output power from all assets must be equal the system load $p_{\text{ld,t}}$ plus the charging power.	$p_{\text{ld,t}} = \sum_g P_{g,t} + \sum_i p_{i,t} + \sum_s (p_{\text{dc,s,t}} - p_{\text{ch,s,t}})$
Reserve Margin: The dispatchable capacity must be larger equal the planning reserve margin $\max_t p_{\text{ld,t}} \cdot 1.15$.	$\max_t p_{\text{ld,t}} \cdot 1.15 \leq \sum_r P_r$ with $r \in \{g, s\}$
Capacity Control	
Constrain capacity additions to exogenous limits	$P_{\text{new,r}} \leq P_{\text{new,r}}^{\text{max}}$ and $P_{\text{new,r}} \geq P_{\text{new,r}}^{\text{min}}$ with $r \in \{i, g, s\}$
Constrain storage energy capacity additions	$E_{\text{new,s}} \leq E_{\text{new,s}}^{\text{max}}$ and $E_{\text{new,s}} \geq E_{\text{new,s}}^{\text{min}}$
Constrain total capacities	$P_r \leq P_r^{\text{max}}$ and $P_r \geq P_r^{\text{min}}$ with $r \in \{i, g, s\}$
Constrain total storage energy capacity	$E_s \leq E_s^{\text{max}}$ and $E_s \geq E_s^{\text{min}}$
Constrain capacity retirements	$P_{\text{rem,r}} \leq P_{\text{rem,r}}^{\text{max}}$ and $P_{\text{rem,r}} \geq P_{\text{rem,r}}^{\text{min}}$ with $r \in \{i, g, s\}$
Constrain retirements of storage energy capacity	$E_{\text{rem,s}} \leq E_{\text{rem,s}}^{\text{max}}$ and $E_{\text{rem,s}} \geq E_{\text{rem,s}}^{\text{min}}$
Constrain energy-to-power ratio to upper limit ep_{max}	$E_s \leq ep_{\text{max}} P_s$
Constrain energy-to-power ratio to lower limit ep_{min}	$E_s \geq ep_{\text{min}} P_s$

Calculate the **total power capacity** as the sum of the initial capacities $P_{0,r}$ and the capacity additions $P_{\text{new},r}$, minus the retired capacity $P_{\text{rem},r}$.

$$P_r = P_{0,r} + P_{\text{new},r} - P_{\text{rem},r} \quad \text{with } r \in \{i, g, s\}$$

Calculate the **total storage energy capacity** as the sum of the initial capacities $E_{0,s}$ and the capacity additions $E_{\text{new},s}$, minus the retired capacity $E_{\text{rem},s}$.

$$E_s = E_{0,s} + E_{\text{new},s} - E_{\text{rem},s}$$

Storage Operation

The **storage charging state** during the time slot t is given by the remaining energy from the previous slot, reduced by the leakage losses, plus the newly charged

$$e_{s,t} = (1 - \eta_{s,\text{leak}})^{0.5(d_t + d_{t-1})} \cdot e_{s,t-1} + (\eta_s p_{\text{ch},s,t} - p_{\text{dc},s,t}) d_t$$

Storage energy capacity constraint: the charged energy is limited by the installed capacity times the depth of discharge

$$e_{s,t} \leq E_s d_{0,s}$$

Storage power capacity constraint: the charging and discharging power are limited by the installed capacity

$$p_{\text{ch},s,t} \leq P_s \quad \text{and} \quad p_{\text{dc},s,t} \leq P_s$$

Variable Generator Operation

Variable generator capacity constraint: the output power is limited by the installed capacity times the capacity factor during time slot t

$$p_{i,t} \leq P_i c_{f,i,t}$$

Generator Operation

Generator capacity constraint: the output power is limited by the installed capacity

$$p_{g,t} \leq P_g$$

Generator energy constraint: the yearly output energy is limited

$$\sum_t d_t p_{g,t} \leq E_{g,\text{max}}$$

Generator capacity factor constraint

$$\sum_t d_t p_{g,t} \leq 8760 c_{f,g,\text{max}} P_g$$

Hydropower Operation Control

The **energy remaining in the reservoirs at the end of each month** m is equal the remaining energy from the month $m - 1$ plus the monthly inflow ($e_{\text{HY},\text{in},m}$ times the yearly electricity production), minus the total output during the hours t_m comprising the month m

$$e_{\text{HY},m} = e_{\text{HY},m-1} + e_{\text{HY},\text{in},m} \sum_t d_t p_{\text{HY},t} - \sum_{t_m} d_{t_m} p_{\text{HY},t_m}$$

The **impounding reservoir capacity poses an upper limit** to the maximum stored amount of energy (expressed as a fraction 0.934 of the maximum monthly inflow)

$$e_{\text{HY},m} \leq \max_m \{e_{\text{HY},\text{in},m}\} \sum_t d_t p_{\text{HY},t} \cdot 0.934$$

Lower limit of the saved energy ($e_{\text{HY},\text{min},\text{frac},m} = 0.75$ for $m = \text{June}$)

$$e_{\text{HY},m} \geq \max_m \{e_{\text{HY},\text{in},m}\} \sum_t d_t p_{\text{HY},t} \cdot e_{\text{HY},\text{min},\text{frac},m}$$

Lower limit on the relative difference between months

$$e_{\text{HY},m} \geq e_{\text{HY},m-1} \cdot 0.5$$

Policies

The amount of electric energy defined by the **RPS target** ξ_{rps} as a fraction of the total yearly demand must be produced from eligible generators.

$$\xi_{\text{rps}} \sum_{t,r} d_t p_{r,t} \leq \sum_{t,i} d_t p_{i,t} + \sum_{t,g_{\text{rps}}} d_t p_{g_{\text{rps}},t}$$

with $g_{\text{rps}} \in \{\text{geothermal, biomass}\}$ and $r \in \{i, g, s\}$

The **total storage power capacity** must be equal the exogenous target.

$$\sum_s P_s = P_{s,\text{target}}$$

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