THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Learning by modeling energy systems

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Abstract

Meeting the 2°C climate target would likely require reducing carbon dioxide emissions from the global energy system to virtually zero within 50-100 years, and within 30-50 years for the 1.5°C target. Both cases would involve a complete transition of the global energy system to zero-emission technologies like renewables or nuclear power at unprecedented rates. This complex challenge can only be analyzed with energy system models, i.e. large computer models that can generate future energy scenarios. This thesis presents five papers that develop methodology for modeling the global energy transition.

In papers 1-2, we develop new methods for representing technological development of emerging technologies like solar or wind power in energy models. We use "experience curves", empirical relationships that describe how costs tend to fall for new technologies as a function of their market growth. We find that by investing in solar and wind at a global scale we can drive down costs to a point where they compete with conventional fossil energy sources.

Paper 3 is a study of meeting climate targets with bioenergy with carbon capture and storage (BECCS) using an integrated energy-climate model. BECCS is a technology that can produce negative emissions; i.e., it can deliver energy while actively removing CO_2 from the atmosphere. We find that if BECCS is used on a global scale, it can significantly reduce costs of meeting the 1.5°C target and potentially reverse global warming in the long run.

Paper 4 addresses another modeling problem. Many global energy models are too large to use an hourly time resolution which may be necessary to represent very high penetration levels of variable renewables like solar and wind power. We present a method called "resource-based slicing" that can capture sufficient variability in just 16 annual time periods.

Finally, in paper 5, we develop an open-source code base that uses global meteorological datasets to generate all input data an energy model needs to study solar-, wind- and hydropower in arbitrary world regions. Our GIS-based approach produces both hourly capacity factors and regional potentials for installed capacity,

and our simple generic model performs on par with more detailed dedicated models of European electricity generation.

Keywords: energy system models, experience curves, BECCS, negative emissions, climate targets, time slices, variable renewables, GIS, open source, reanalysis

List of publications

Paper 1

Mattsson N & Wene C-O (1997). Assessing new energy technologies using an energy system model with endogenised experience curves. Int. J. Energy Research 21(4): 385–393.

Paper 2

Mattsson N (2002). Introducing uncertain learning in an energy system model: a pilot study using GENIE. Int. J. Global Energy Issues 18(2-4): 253–265.

Paper 3 + supplementary material

Azar C, Johansson DJA and Mattsson N (2013). Meeting global temperature targets—the role of bioenergy with carbon capture and storage. Environ. Res. Lett. 8(3): 034004.

Paper 4

Lehtveer M, Mattsson N and Hedenus F (2017). Using resource based slicing to capture the intermittency of variable renewables in energy system models. Energy Strategy Reviews 18: 73–84.

Paper 5 + supplementary material

Mattsson N, Verendel V, Hedenus F and Reichenberg L (2019). An autopilot for energy models – automatic generation of renewable supply curves, hourly capacity factors and hourly synthetic electricity demand for arbitrary world regions. Submitted to Energy Strategy Reviews.

Not included in the thesis

Licentiate thesis

Mattsson N (1997). Internalizing technological development in energy systems models. Thesis for the degree of Licentiate of Technology, Chalmers University of Technology.

Paper

Reichenberg L, Hedenus F, Mattsson N and Verendel V (2019). Deep decarbonization and the Supergrid – prospects for electricity transmission between Europe and China. In preparation.

Acknowledgements

Paraphrasing Newton: if I have barely passed the bar, it is only by having been hoisted by the rear end by colleagues.

I owe two colleagues in particular my gratitude. My first supervisor at the division of Energy Systems Technology, Professor Clas-Otto Wene, has always possessed the gift of being 2-3 years ahead of the rest of the scientific community. On my first day of work as a PhD candidate in 1996, a fully-formed research question burst out of his head like Athena: how would the dynamics of energy models change if we could internalize technological development using experience curves? I will never forget his enthusiasm some weeks later when I showed him preliminary results that featured different locally optimal pathways for the future energy system (paper 1). He literally went on to write a book highlighting our findings (Wene 2002). After a flying start like this, a normally gifted PhD candidate would have received his doctorate with accolades within two years.

The second colleague that deserves special mention is Associate Professor Fredrik Hedenus, current head of the division of Physical Resource Theory, who has acted as a close facsimile to a thesis advisor for the few past years while simultaneously treating me as a senior researcher. He has personally ensured the completion of this thesis by finding financial support for my work, observing from some distance when things were progressing and lighting fires otherwise, and spending his own research time applying finishing touches to paper 5 and proofreading my thesis. I owe you a beer Fredrik, perhaps even two.

When I joined the division of Physical Resource Theory (PRT) around 2011, I had 15 years of experience as an energy system modeler, including about 6 years working for the International Energy Agency. Despite this background, I filled many knowledge gaps and had numerous new insights about energy and climate dynamics thanks to all my colleagues at PRT, but most notably from Professor Christian Azar. Our collaboration on the master course Sustainable Energy Futures has done more than anything else for my understanding of energy and climate, and more importantly for my development as a teacher.

Moreover, my sincere thanks...

- ...to the three musketeers and d'Artagnan at Energy Systems Technology for moral support and having each other's backs when the rest of the company suddenly began melting away around us
- ...to other coauthors of the enclosed papers not mentioned above, who also deserve partial credit for this work – Daniel, Mariliis, Ville and Lina (bonus thanks to Lina who also pulled extra weight in the past weeks)
- ...and finally to all colleagues at PRT, close friends and family, for offering a unique mix of support, encouragement and well-deserved mockery during my record-setting 23-year procrastination.

This thesis is dedicated to Alison and Smilla, in the hope that they don't feel the need to assign climate blame to anyone 50 years from now. Or at least that they don't blame me.

Göteborg, December 2019

Niclas Mattsson

Contents

1 Introduction

If humankind truly aspires to stop global warming and stabilize global temperature at some level, regardless of when and at which temperature level we agree to stabilize, then we must reduce carbon dioxide (CO_2) emissions to near-zero (Allen et al., 2009; Matthews and Caldeira, 2008). Additionally, if we decide to limit warming to 2°C above preindustrial temperature levels with reasonable likelihood, then near-zero emission levels need to be reached well before the year 2100. For the more ambitious 1.5°C target, emissions must likely be reduced to zero around 2050[1] (IPCC 2018). Either target requires a major shift to some combination of renewables, nuclear power and carbon capture and storage (CCS), at unprecedented rates of transition for the global energy system (Smil, 2010).

But although many may (rightly) think of climate change as one of the greatest challenges society has ever faced, it is not the only engineering challenge confronting the global energy system. It is hard to fault many developing countries for focusing on providing their citizens with modern energy carriers, even when this increases their dependency on fossil fuels. The quality of air in some cities is so unhealthy that average life expectancy has fallen several years, although possible solutions to this problem may intersect with those of the climate problem. Energy security remains a concern for countries with limited resources of their own.

On a more hopeful note, market growth rates of solar and wind power during the past 10-20 years have surpassed even the most optimistic scenarios produced by environmental NGOs. But this brings new challenges in itself; maintaining high reliability of electricity supply will test power system engineers as these variable renewables continue to gain market share.

[1] Since temperature level is a function of cumulative CO_2 emissions, the deadline year depends on the pathway to zero emissions.

The problems facing the energy system are complex, interconnected and transdisciplinary. Understanding energy systems often requires straddling fields of engineering, economics, environmental science, systems theory, and – for modelers like myself – operations research (a branch of mathematics) and computer science.

Further compounding the situation is the fact that it is virtually impossible to perform experiments. We have no backup earth to subject to scientific climate prodding. Testing micro-scale energy systems may have little relevance to behavior of full-scale systems.

For all these reasons, the only practical recourse available is modeling. But despite the limitations of a virtual playground, the questionable applicability on the real world, and the many, many uncertainties that we modelers are so painfully aware of, studying models is quite literally our only path forward.

1.1 Energy system models

An energy systems model can be characterized as a simplified, formalized representation of a real energy system, usually described using mathematical relations. Models mainly serve as a tool for learning; perhaps first for modelers themselves but ultimately for policy-makers and the general public. They can also provide decision support in specific planning situations.

Although the use of models often involves looking into the future, the purpose is not to deliver forecasts of the likely development of the energy system. Instead, the ideal function of models is to answer hypothetical "what-if" questions, thereby generating qualitative or quantitative insights into the studied system. Some advantages of using a formal model-based methodology are that it adds consistency, reproducibility and a common platform for communication to the analysis.

There are many different types of energy system models. Hall and Buckley (2016) use 14 different *dimensions* to categorize energy models used in the UK. One common classification is "top-down" and "bottom-up" models[2]. Top-down models refer to macro-economic models that use aggregated production functions and focus on market interactions. These are beyond the scope of this thesis.

We focus on bottom-up or systems engineering models. These are technology-oriented models that explicitly describe technical change within the energy system by including a large portfolio of potential technologies. Technological options are specified using both technical and cost parameters. In economic terms they are

[2] van Vuuren et al. (2009) provides a detailed comparison of differences between results related to IPCC AR4 from top-down and bottom-up models.

usually partial equilibrium models, because economic effects in non-energy sectors are largely ignored. For example, solar PV capacity may grow significantly in a model run, but opportunity costs for using capital and labor to build this industry are not taken into account.

An optimization model is an energy model that is formulated as a mathematical optimization problem, i.e. it maximizes or minimizes an objective function subject to a number of constraints. The most common objective is to maximize the sum of producer and consumer surplus. However, when energy demand is inelastic (i.e. is independent of energy prices), this is equivalent to just minimizing total system cost. The optimal solution reflects a market equilibrium under perfect competition and may therefore underestimate real world costs. It represents the point of view of a single decision maker, an actor who minimizes total costs from a society point of view. This holds even when there are multiple regions and sectors in the model.

Optimization models can range in scope from detailed power dispatch models with unit commitment and operational constraints, to long-term dynamic planning models with time horizons of 50-100 years. Much of the art of modeling lies in exploring the trade-offs between technological, spatial and temporal detail, and adapting system boundaries and model structure to the current research question.

Perhaps surprisingly, useful energy system models can be formulated entirely using linear equations of continuous variables. Such models are called linear programming (LP) models. This requires that both the objective and all constraints are linear functions. A significant advantage of LP models is that extremely efficient solution algorithms are available (using interior-point methods), so that even problems with millions of variables and equations can be solved.

1.2 Thesis objective and synopsis

The overriding goal of the thesis is to develop methodology for energy system models to help understand the transition of the global energy system toward a zero-carbon future. Specific research questions will be presented in each chapter for each individual study. In most cases we had a fairly well-defined modeling approach in mind as we commenced the research. This means that on a pragmatic level, the only general research question these studies have in common is: how can we make it work, and how does this change our understanding?

The following is a brief overview of the thesis and its included papers. To help structure the discussion I refer to figure 1-1, which presents a conceptual view of the technical energy system in relation to four critical factors in the system environment (Wene and Rydén, 1988). The main factors are energy demand, energy sources, physical environment and technological development. The figure is not

intended to be comprehensive – for example, there are also significant interactions with the economy and political constraints on the energy system from society – but it provides a useful overview of factors energy modelers must contend with. It was held as a cornerstone of energy modeling at my department during my formative years as a young PhD candidate.

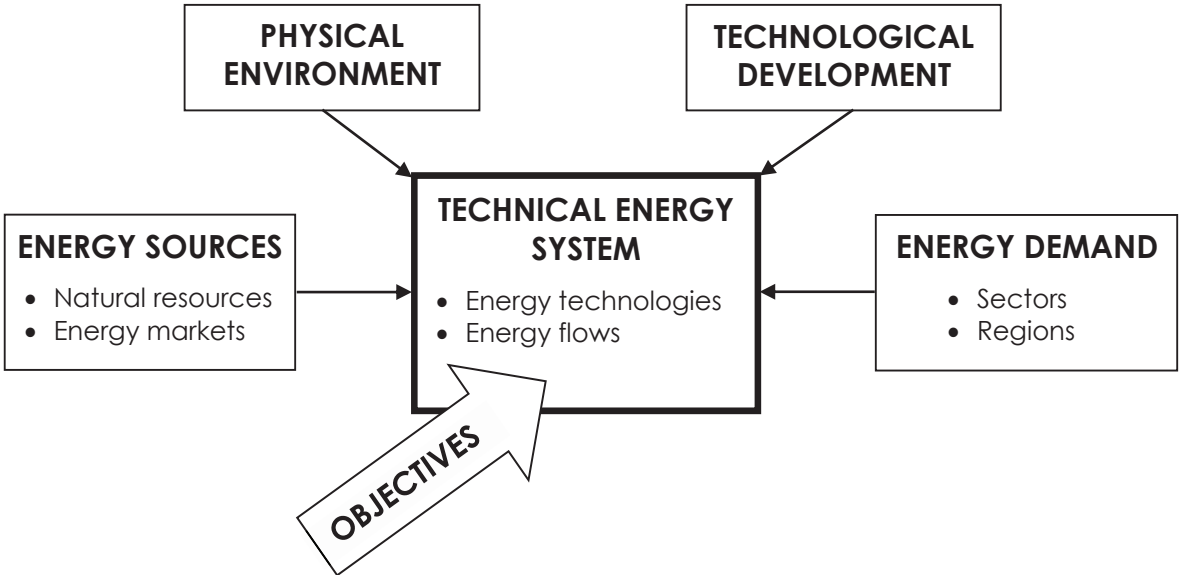

Figure 1-1. The technical energy system and four factors in the system environment.

Chapter 2 summarizes paper 1 (Mattsson and Wene, 1997) and is the first of three chapters that concerns endogenous technological learning (ETL), a method for internalizing technological development in energy system models (c.f. figure 1-1) using experience curves. ETL is especially important for emerging technologies like solar PV and wind power, for which substantial technical progress is expected during the 50-100 year time horizon of the models. In paper 1 we report results from an experimental energy model with experience curves (a.k.a. learning curves). We add a new feedback mechanism that represents induced technological change, as opposed to using exogenous assumptions, and discuss the qualitatively new insights that can arise from this kind of model.

In chapter 3, I discuss research published in my licentiate thesis (Mattsson, 1997). Here I present a more reliable implementation of the same experience curve model as in paper 1. The formulation demonstrated here subsequently became the standard approach to ETL in bottom-up models.

One of the main concerns with ETL models is the impact of uncertainty of the learning rate, a parameter that describes how quickly cost reductions occur as a function of accumulated experience. In chapter 4, I summarize a stochastic programming

model of ETL that endogenously considers learning rate uncertainty and finds technological pathways that hedge against this uncertainty (paper 2) (Mattsson, 2002).

Chapter 5 moves on to the next box in figure 1-1, the physical environment. In this chapter I discuss paper 3 (Azar et al., 2013), which uses a global integrated energy-climate model to study the potential impact of bioenergy with carbon capture and storage (BECCS). BECCS is a technology that can potentially provide negative emissions, which means it can play a unique role in meeting global temperature targets and potentially even reverse global warming. In paper 3 we examine the role of BECCS in meeting various types and levels of climate targets, and its particular economic properties as a mitigation technology.

In chapter 6 we focus on the center box and dive deeper into how to represent a critical aspect of the technical energy system in models, namely the internal representation of time. Conventional bottom-up models use "time slices" to capture demand variability within a model year while reducing the number of time periods from 8760 hourly periods per year to typically just 6-12. The reduction is a prerequisite for solving very large energy models. However, this method is inadequate for systems with high penetration of renewables, because it fails to capture solar and wind variability. In paper 4 (Lehtveer et al., 2017) we devise a conceptually simple alternative called "resource-based slicing" and test its applicability for global energy models and integrated assessment models.

Finally in chapter 7, we shift attention to the left-most box and present a method and an open-source code base for input data generation of renewable energy sources (paper 5) (Mattsson et al., 2019). We use global meteorological reanalysis data combined with other public datasets to generate regional potentials and capacity factors for solar-, wind- and hydropower. Our approach allows us to construct a capacity expansion model of a generic electricity system with hourly dispatch for arbitrary world regions. We test our framework by comparing results with studies by other researchers of future European electricity generation with high penetration of renewables.

2 Endogenous learning in energy system models (paper 1)

"One of the most complex and salient questions remaining in climate change policy modeling is the appropriate treatment of technological change. The approach to modeling technological change is widely considered to be one of the most important determinants of the results of climate policy analyses; that is, the level of emissions abatement that can be achieved at a given cost." (Gillingham et al., 2008)

2.1 Learning-by-doing and experience curves

The term learning-by-doing reflects qualitatively that performance tends to improve, and/or cost tends to decrease, as experience of production increases. Although learning effects were first discovered in the airplane manufacturing industry in the 1930s, the credit for recognizing the far-reaching economic consequences of learning-by-doing is usually attributed to the Nobel laureate Kenneth Arrow, who put forward the hypothesis that technological change in general can be ascribed to experience (Arrow, 1962). Today, learning-by-doing is generally regarded as a prerequisite for performance improvements and cost reductions (Nakicenovic, 1996).

An experience curve (sometimes called a learning curve[3]) is the quantitative embodiment of learning-by-doing. It is an empirical relation stating that costs of a technology decrease exponentially as experience increases. The underlying rationale is that more opportunities for reducing costs and improving performance

[3] We follow Ayres and Martinàs (1992) in our distinction of learning curves and experience curves. Whereas learning curves often refer to learning by labor in repetitive manufacturing processes, the more general experience curves also reflect other changes that occur over the life cycle of a technology, such as incremental design improvements, manufacturing developments and economies of scale.

will be found as more development efforts are committed to a technology. Conversely, the better the price/performance of a technology, the more investments it will attract. In practice, to facilitate data acquisition, selling price is often used as a proxy for costs, and cumulative installed capacity as a proxy for experience.

Experience curves are empirically very well corroborated and have been observed in a wide range of industrial products, processes and technologies, e.g. automobiles, semiconductors, petrochemicals, long-distance telephone calls, synthetic fibers, airline transportation, insurance administration and limestone crushing (Abell and Hammond, 1979; Argote and Epple, 1990; Ayres and Martinàs, 1992; Azar and Dowlatabadi, 1999; Grubler, 1995; Löschel, 2002).

Figure 2-1 shows an experience curve for crystalline silicon photovoltaic (PV) solar cell modules. The long-term stability of the cost reductions, even over six orders of magnitude of increasing experience, is remarkable. This regularity lends support to the notion of using experience curves to extrapolate existing technological development trends into the future. Ausubel (1995) noted generally that rates of technical change in many fields (e.g. communication bandwidth trends, lighting efficiency improvements or global energy decarbonization rates) tend to be stable over very long periods of time, and suggested that many trends could be usefully extrapolated 100 years into the future.

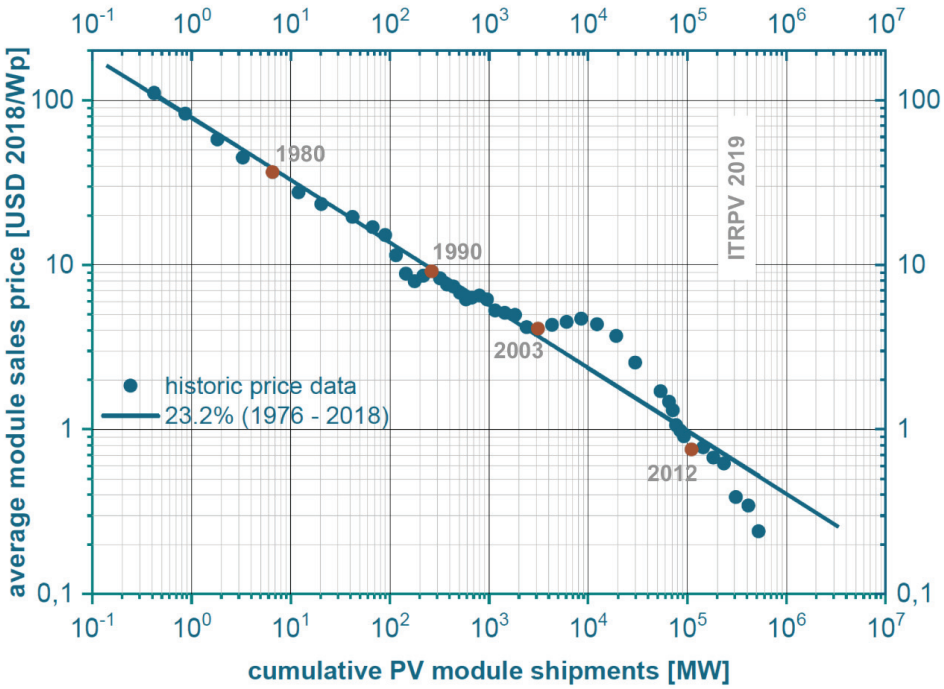

Figure 2-1. Experience curve for crystalline silicon PV modules, 1976-2018 (ITRPV, 2019). Most points are end-of-year observations, but some semiannual points are used between 2003 and 2012.

The experience curve has a simple mathematical formulation:

$$C(E) = \frac{c_0}{\left(\frac{E}{e_0}\right)^{\alpha}} \quad \text{with } \alpha \text{ given by} \quad \mathrm{LR} = 1 - \frac{1}{2^{\alpha}} \qquad \text{(Eq. 1)}$$

Here $C(E)$ represents the specific investment cost (in e.g. €/W for an energy supply technology) as a function of cumulative experience E (in W). The exponent α determines the rate of cost reductions and is frequently expressed using the so-called learning rate LR. A learning rate of 20% (LR = 0.20) means that costs are reduced by 20% for each doubling of cumulative experience. The constants c_0 and e_0 fix a starting point for the curve.

The rate of cost reduction varies significantly between technologies, with typical learning rates for energy supply technologies ranging from 5% to 25% (Weiss et al., 2010). Neij (2008) finds that small, modular technologies such as solar PV or wind power tend to have higher learning rates than large-scale non-modular plants and suggests that modularity may increase opportunities to improve technology and reduce costs.

2.2 Background and research question

The main purpose of energy systems engineering models is to provide decision support to energy policy by studying the dynamics of technical change in the energy sector. In traditional models however, improvements in individual technologies can only be considered by exogenous assumptions of cost reductions and/or efficiency improvements over time. The models are therefore by design blind to possibilities of learning-by-doing, i.e. technological development induced by actual market implementation and experience. This deficiency is especially significant for emerging technologies, which hinge critically on future development prospects.

Although costs for developing technologies can be ambitiously parameterized even in standard models, two main problems may arise when exogenous cost assumptions are used. First, to quote Niels Bohr, forecasting is difficult – especially about the future. Experience curves may lend some support to cost extrapolation which is inherently uncertain, but exogenous cost forecasts cannot directly utilize experience curves since future capacity investments are also unknown. Second, traditional energy models often feature perfect foresight over time horizons of several decades. With exogenous cost reductions, the model can then defer investments until they are profitable in a later time period, when in reality costs are unlikely to fall significantly unless large-scale investments take place. This manifests as an inconsistency, when consistency is otherwise a major selling point of energy models.

A pragmatic way of dealing with this problem is to limit technology growth rates. The idea is that if the model "wants" to make large capacity investments at some point in the future, then it is forced to begin investing well in advance, presumably during a period of higher cost.

If exogenous investment cost trajectories are used, the degree of development of a technology is independent of actual activity of that technology within the model, which corresponds to an autonomous view of technological development. This may be acceptable for applications where most technological development occurs outside the borders of the system being studied, e.g. a study of a national energy system where most cost reductions occur on the international arena.

In economy-oriented models, technical change is often accounted for by including a parameter called the Autonomous Energy Efficiency Improvement (AEEI). The AEEI gives the rate at which the energy intensity of the economy can be reduced by structural change and penetration of new technologies, independently of energy prices (Manne and Richels, 1992; Nyström, 1995). The parameter is specified exogenously, and is in the range of 0-1 %/year in most studies (Azar, 1996).

This can be contrasted to a view of induced technical change, in which technologies and systems adapt to accommodate external pressures (e.g. Azar and Dowlatabadi, 1999; Grubb, 1997; Nakicenovic, 1996). In this view governments can use policy instruments to harness the private sector and create new markets that enable learning-by-doing.

Induced technical change can be reflected in bottom-up models by directly relating investment costs to accumulated experience of a technology using experience curves. These curves quantify learning-by-doing in a simple and transparent manner and are empirically well established. However, they are also have a non-convex shape, so considerable computational difficulty should be expected from an effort to implement them in energy systems models. Nevertheless, they also represent a fundamental shift in model dynamics since the model "knows" that it can use investments to drive down costs.

This leads us to the following research questions for paper 1:

- How can we implement nonlinear experience curves within the framework of linear bottom-up energy system models?
- Can the expected computational difficulties be overcome (or at least bypassed)?
- What qualitatively new insights can arise from a model with endogenous learning?

2.3 Method

There are two main approaches to integrating experience curves within energy systems models based on linear programming:

1. Direct nonlinear implementation
2. Piecewise linear approximation of cumulative costs, after variable separation of the cost function

Method 1 is the most straightforward. The experience curve cost relation $C(E)$ in equation 1 replaces the specific technology costs $c_{k,t}$ (€/kW) in the objective function of the model. The new objective will then contain multiplicative terms of the form $C(E_{k,t}) \cdot I_{k,t}$, where $E_{k,t}$ is the cumulative experience of technology k at time t, and $I_{k,t}$ is the capacity investment (in kW) of technology k at time t. Since both $E_{k,t}$ and $I_{k,t}$ are variables, this results in a nonlinear (and nonconvex) minimization problem. Standard nonlinear solvers can be used to find solutions for this problem.

This was the approach chosen for paper 1. This method is attractive because of the simplicity of the model formulation. However, the main disadvantage is that most nonlinear solvers appropriate for large-scale problems use gradient methods which only find locally optimal solutions. When applied to nonconvex objective functions there is no guarantee (and no efficient way of confirming) that any local optima found also is a global optimum. To increase the confidence that the best locally optimal solution discovered was in fact the global optimum, we explored the solution space by performing several model runs using different initial values for the variables.

The GENIE model

The GENIE[4] model is a bottom-up model of the Global ENergy system with Internalized Experience curves. It is intended as an experimental model to demonstrate the feasibility of large-scale energy system models with endogenous experience curves, and to illustrate the type of insights that can be obtained from models with improved technological dynamics.

The model scope is therefore limited to the electricity supply sector. Neither heat, industrial feedstock, transport nor other demand-side technologies are included in the model.

There are twelve electricity supply technologies in the model, six of which have experience curves. Four world regions are represented and the model time horizon is

[4] A genie or djinn is a spirit from Arabian tales, e.g. the spirit in the lamp in the tale of Aladdin. No allusion to the German word is intended.

80 years (1995-2075). Note that only results to 2055 are shown in the figures below (the last time period is 2045, but all periods have a length of ten years). The extra time periods are included to account for "residual learning", i.e. the future benefits of having developed a technology compared to not having done so.

The most important model constraints are:

- **Energy balance:** total electricity generation must exceed demand.
- **Capacity limit:** electricity generation is limited by installed capacity.
- **Peak & reserve requirements:** "extra" capacity is required for peak and reserve demands.
- **Growth restriction:** technology growth is limited to 30%/year.
- **Expansion potential:** regional wind- & hydropower resources are limited.
- **Intermittent generation limits:** solar PV and wind power can only supply 20% of annual electricity generation individually, or 30% combined.
- **CO_2-emissons limit:** total CO_2-emissions from electricity can be limited.
- **Fossil fuel supply curves:** fossil fuel costs increase as resources are depleted.

Wind power and solar PV are intermittent, but the combination technology PV-H2 is not considered intermittent. The latter consists of solar PV, electrolysis of water into hydrogen and oxygen, storage and recombination in fuel cells.

The model minimizes the total discounted cost of global electricity supply with perfect foresight. See Mattsson (1997) for more information on the GENIE model and a complete listing of the model code.

2.4 Results

In my licentiate thesis (Mattsson, 1997) I replicated the early pilot study in paper 1 with a reworked model based on the piecewise-linear methodology described in the next chapter. Two new technologies (wind power and combined cycle gas turbines) were added to the new model, and the number of technologies with experience curves was increased from two to six. Results from the newer model are included here, as they are functionally identical to the results using the nonlinear implementation of paper 1.

Results from the base scenario assumptions without CO_2 restrictions appear in figure 2-2. This can be described as a business-as-usual development of the global electricity system, with total discounted system costs of 9117 billion USD. In this solution, conventional fossil technologies are phased out and initially replaced by CCGT and hydropower. Later, due to increased gas prices, CCGT is replaced by a

mix of advanced coal power, wind and nuclear power. CO_2-emissions from this system roughly double by the middle of the century compared to 1995 levels. However, the pathway in figure 2-2 is merely a locally optimal solution. Due to the nonlinearity of the experience curve, other solutions exist that arise from the exact same set of underlying parameter assumptions.

An alternative solution to the same scenario appears in figure 2-3. This solution has a total system cost of 9106 billion US$, marginally lower than the previous solution, and is the true global least cost optimum. This case is initially similar to the previous one, except that CCGT has a less prominent role and that investments in solar PV and fuel cells take place "behind the scenes". After 2015, however, the two cases visibly diverge. In case 2, natural gas fuel cells swiftly gain market share and eventually become the largest source of electricity. This development occurs at the expense of CCGT, advanced coal and nuclear power. Also, solar PV contributes substantially to global electricity generation. Together with wind power, they reach the upper limit for intermittent power sources in GENIE. The non-intermittent PV-H2 technology also enters the system. Total CO_2-emissions increase by a maximum of 30%, but are reduced to just below 1995 levels by mid-century.

It should be emphasized that these alternative futures stem from the same scenario, i.e. input databases and assumptions are identical for both cases. Mathematically they represent two different locally optimal solutions to the same problem (but there are many more).

A hypothetical global policy maker that hesitates between these trajectories must decide early: in case 1, there are no investments in PV or fuel cells. In case 2, these technologies grow at the maximum allowed rate from the first time period onward. These investments are not profitable when they occur. They are necessary to drive down costs for PV and fuel cells in the long run. This situation is illustrated in figure 2-4, which shows annual investment cost profiles for the two solutions.

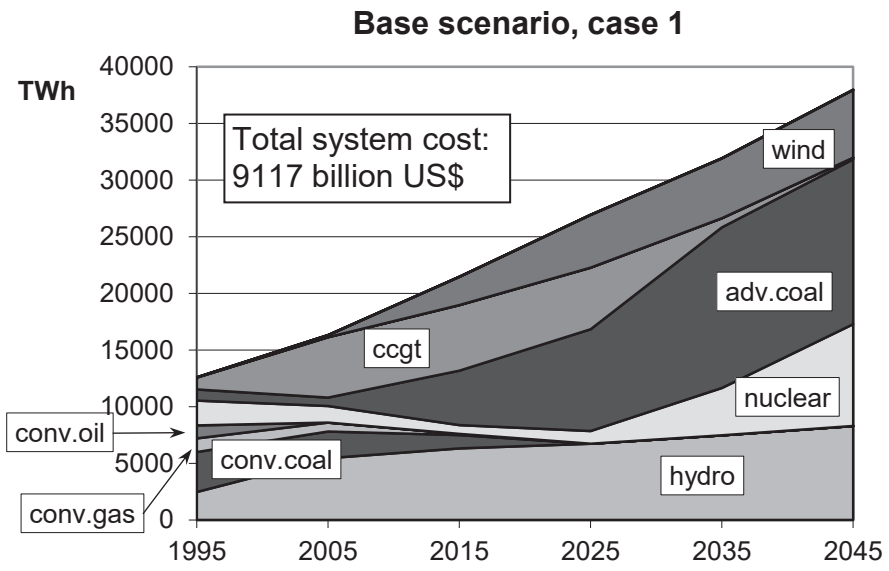

Figure 2-2. Global electricity generation by technology in the base scenario: case 1, a business-as-usual situation.

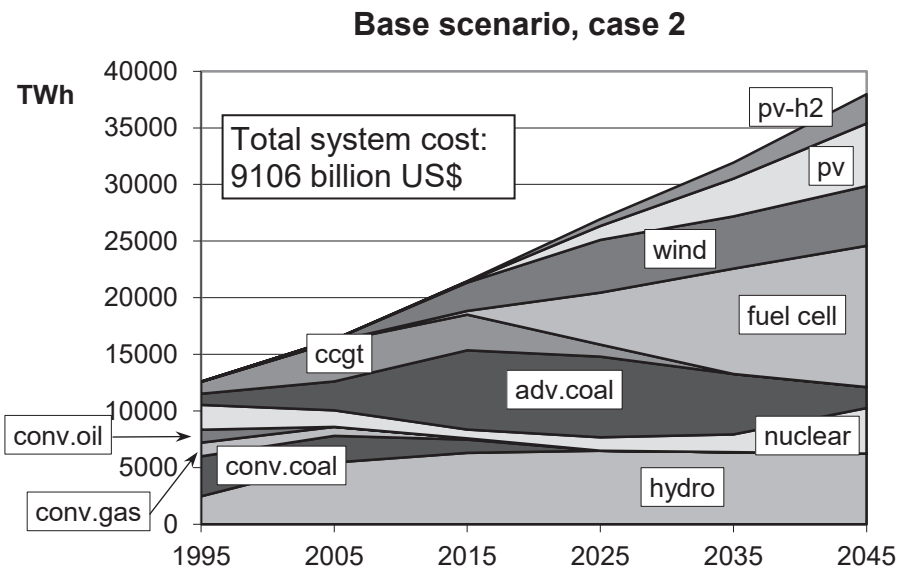

Figure 2-3. Global electricity generation by technology in the base scenario: case 2 (optimal), a more diverse system.

Figure 2-4 shows that case 2 requires approximately 30% more investment capital than case 1 in the year 2025. The difference between the cases represents additional learning investments (Wene, 2000) that are required in order to develop the emerging technologies. This suggests that there is a risk of technology lock-in. If capital is a scarce resource in the future (a fairly safe assumption), there is a danger that capacity will be built up with established technologies as in case 1, and no cost reductions will take place in the emerging technologies. The model avoids this situation by the perfect foresight mechanism, but the real world situation requires technology specific policy instruments or niche markets that bear the additional costs of developing the new technologies.

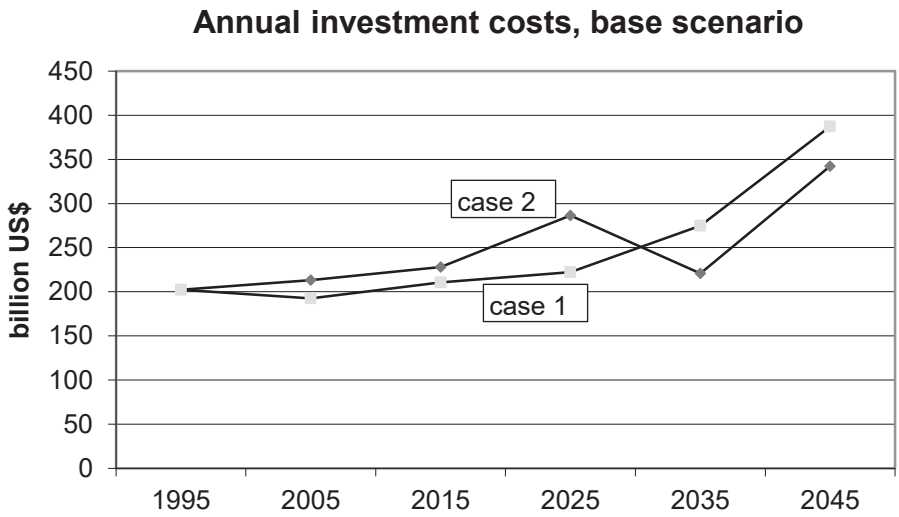

Figure 2-4. Annual investment costs for the base scenario.

The trade-off between the need for near-term learning investments in order to develop low cost technologies in the long term emphasizes the importance of discount rates in models with endogenous technological learning. The "standard" value of 5% per year used in GENIE and many other energy system models with long time horizons is arguably too high. To illustrate numerical consequences with a simple example, a 5% discount rate values costs that occur 80 years in the future about 50 times lower than costs that those that occur today ($1.05^{80} = 49.6$). Since our society has a much longer life expectancy than individual humans or companies, some claim (e.g. Azar and Sterner, 1996; Stern et al., 2007) that it may be motivated to set the pure rate of time preference (ρ) to zero. According to the Ramsay rule (e.g. Moore and Vining, 2018), the social discount rate would then only reflect expected future economic growth (g) and the elasticity of the marginal

utility of consumption (η). In Mattsson (1997) alternative model runs were performed with a discount rate of 2% per year (corresponding to ρ=0, g=1.5% per year and η=1.33). The resulting technology trajectories were very similar to case 1 and case 2, but the total system cost for case 2 was 7% lower than case 1 (instead of virtually identical).

2.5 Method conclusions

One of the headline results of paper 1 was the existence of multiple local optima. In retrospect, choosing the straightforward nonlinear implementation may have been fortunate because it led to this discovery, while a competing research team at IIASA did not report local optima in their simultaneous paper using an experience curve model (Messner, 1997).

However, the nonlinear solver was sensitive to initial conditions and converged to different local optima somewhat unpredictably, and occasionally failed entirely. It was also rather slow compared to linear solvers. For these reasons, we decided to reimplement the model using a piecewise linear approximation of the experience curve (i.e. method 2 above). This approach had several advantages: it found locally optimal solutions relatively quickly and consistently, it did not depend on initial variable values and it could determine when the global optimum had been found. The implementation is described in more detail in the next chapter.

An alternative solution approach to the nonlinear formulation would be to apply global optimization techniques. There are algorithms for concave minimization that may prove to be efficient for our problem, but since we obtained satisfactory results using method 2, we never experimented with nonlinear global optimization.

2.6 Discussion and recent research on experience curves

Ayres and Martinàs (1992) demonstrate that learning rates are not always constant over time. Experience curves occasionally display separate phases with different learning rates. They explain these slope changes in terms of the technology life cycle. An initial period of slow decline in costs may correspond to the infancy and childhood stages of the technology life cycle, followed by a swifter rate of progress as the adolescent stage is entered and the technology reaches a larger commercial market. Wene (2000) also discusses discontinuities in experience curves, but differentiates between breaks in experience curves based on cost data and on price data. He calls those based on cost data *technology structural changes* and hypothesizes that they are caused by radical changes in the development process, e.g. a new variant of the technology or a major change in the way the technology is produced.

Wene labels discontinuities in experience curves based on price data *market structural changes.* These breaks reflect a change in market conditions, e.g. a dominant firm that reduces its prices to meet increased competition from new actors.

The apparent stagnation between 2003 and 2008 in the solar PV experience curve in figure 2-1 has yet another explanation. The swift growth of the PV industry caused the demand of polycrystalline silicon for PV to exceed the demand for use in semiconductors, which led to a severe worldwide shortage. During this time, increased material cost in PV modules masked ongoing improvements in the rest of the production chain. When the shortage was resolved in 2008, PV prices quickly reverted to the long-term experience curve [ref].

Ayres and Martinàs (1992) also suggest that during the late stages of the life cycle, product standardization may cause learning to cease to be directly related to production experience. Many experience curve analyses adopt this idea by including "floor costs", a lower limit to costs that reflect an end to learning-by-doing (e.g. Hedenus et al., 2006; Kouvaritakis et al., 2000; Kypreos and Bahn, 2003; Seebregts et al., 2000). However, in my opinion the notion of floor costs lacks empirical support in technology studies. It may be that apparently stagnating costs are merely an artefact of market saturation. Once a technology has become widespread, it becomes increasingly difficult to double cumulative experience, and cost reductions may appear to halt. I have yet to see a convincing argument why learning-by-doing should come to an end if experience of production continues to double.

An important issue to consider is the question of system boundaries. What is the learning system? Neij (2008) finds learning rates for wind turbine investment costs in the range of 6–8%, and learning rates for the levelized cost of electricity for wind power around 17%. The latter experience curves include both investment cost reductions for turbines as well as installation cost reductions, efficiency improvements and reduction of operating and maintenance cost. It may appear that both could be appropriate depending on what the system-in-focus happens to be. However, Wene (2000) emphasizes the importance of relating to the same learning system for the performance measure (i.e. cost) and cumulative experience. Relating electricity costs to cumulative installed capacity would be a misuse of the experience curve, because this would be relating the performance of the total system (which produces electricity) to the experience in one of its subsystems (that manufactures turbines). An experience curve for the cost of wind electricity must measure experience in MWh, not MW.

The effects of public and private-sector R&D are usually considered to be implicit within the experience curve representation. However, there have been efforts to quantify R&D explicitly using two-factor learning curves, which disaggregate the

effects of learning-by-doing and "learning-by-searching" (Kouvaritakis et al., 2000). These analyses aid thinking about dynamics of technological development, but suffer in practice by the difficulty of measuring private R&D spending. Patent registrations or other indicators are often used as proxies (Wiesenthal et al., 2012), but this introduces an error that limits the prognostication value of the two-factor approach. Public R&D data is more widely available and has been used to estimate two-factor learning curves for wind energy in European countries (Klaassen et al., 2005).

Nemet (2006) disputes the assumption that experience is the main driver of observed cost reductions in solar PV from 1975 to 2001. He finds that majority of the cost reductions can be attributed to upscaling of module production plants, increasing module efficiency and declining costs of silicon. A natural counterpoint could be that experience is precisely what enables the upscaling or increased efficiency. Nemet raises this counter-argument, but gives examples of firms that increased manufacturing capacity rapidly in spite of having limited production experience, and claims that important efficiency breakthroughs were achieved in universities. However, the upscaling firms were still quite small in absolute terms (e.g. Q-Cells increased production capacity from 12 MW to 50 MW per year in two years), and the capacity increase did not take place in a vacuum – there was arguably considerable spillover of experience from other firms and other sectors (e.g. semiconductor manufacturing) (Wiesenthal et al., 2012). Moreover, scale effects are often regarded as key components of learning-by-doing on a technology level (e.g. Dutton and Thomas, 1984).

A related question is whether experience is a superior predictor of future costs compared to a simple time relation. Nagy et al. (2013) tested this on a database of 62 different technologies and found that both relations had roughly equal predictive value. However, Nagy et al. also noted that the majority of technologies in the database featured exponential growth. As long as a technology grows exponentially, experience curves are indistinguishable from regular cost reductions over time, a fact originally observed by Sahal (1979). To discriminate between the two versions, technologies featuring "stop-and-go" behavior need to be examined. Nuclear power comes to mind as a potential candidate, but unfortunately the cost of nuclear has increased rather than decreased, and is a widely cited example of "forgetting-by-not-doing" (e.g. Grubler, 2010; Rosegger, 1991). Nevertheless, despite the near universal acceptance of experience curves dynamics, it is clear that more empirical support is required.

A major weakness of the experience curve concept is the lack of an underlying theoretical foundation. However, in an intriguing recent development, Wene (2007,

2015) uses a cybernetic approach to study a general learning system and derives the most commonly observed learning rates for real-world technologies. Using simple assumptions – postulating the functional form of the experience curve and assuming that the learning system is feedback regulated and operationally closed (i.e. that external stimuli do not determine internal states of the system) – he calculates the eigenvalues of the learning loop and finds that the first modes appear at 20%, 7% and 4%. These values are in line with literature reviews of technologies that find clusters of learning rates at 18-20% and around 5% (Dutton and Thomas, 1984; McDonald and Schrattenholzer, 2001).

3 Piecewise linear reimplementation (licentiate thesis)

In this section, I describe an alternative method of implementing technological learning in energy system models using piecewise linear approximation of the experience curve. The mathematical implementation was documented in my licentiate thesis (Mattsson, 1997) along with the full code of the GENIE demonstration model. Well-known bottom-up models such as MARKAL and TIMES have subsequently adopted this formulation (Loulou et al., 2005, 2004).

3.1 Research question

Paper 1 demonstrated the general viability of using experience curves to quantify technological learning in energy models, but the nonlinear implementation used was sensitive to initial conditions and solved quite slowly, even in the small demonstration model. Can a piecewise linear approach overcome these difficulties to make experience curves feasible in large-scale real world models?

3.2 Method: piecewise linear implementation

A common method for eliminating certain types of nonlinearities in optimization problems is to approximate the nonlinear functions using piecewise linear segments. Piecewise linearization reduces the problem to either a pure linear program (for convex nonlinearities) or a mixed-integer linear programming problem (for the nonconvex case). This requires that the nonlinearities are separable in its variables, which our model with its multiplicative terms (see section 2.3) unfortunately is not. However, the objective function can be reformulated to become separable in the following manner.

First, recall from section 2.3 that the objective function of a straightforward nonlinear experience curve implementation contains terms of the form $C(E_{k,t}) \cdot I_{k,t}$, where $C(E)$ is the experience curve defined in equation 1 of section 2.1. Now note that $I_{k,t} = E_{k,t} - E_{k,t-1}$. Next, define the cumulative investment cost function $CIC(E)$ as

$$CIC(E) = \int_{e_0}^{E} C(E')dE' = \int_{e_0}^{E} \frac{c_0}{\left(\frac{E'}{e_0}\right)^{\alpha}} dE' \qquad \text{(Eq. 2)}$$
$$= \frac{1}{1-\alpha}(E \cdot C(E) - e_0 \cdot c_0)$$

and replace the terms $C(E_{k,t}) \cdot I_{k,t}$ in the objective with $CIC(E_{k,t}) - CIC(E_{k,t-1})$. (This is not strictly equivalent, but the new term is actually more correct since it avoids a sampling error due to the limited number of time periods.) Since both $CIC(E)$ terms are functions of only one variable, the new objective function is separable and therefore a piecewise linear approximation can be used. Then integer variables can be defined as segment indicators and the resulting problem can be solved using the well-established branch-and-bound method for mixed-integer linear programming (MILP), which has very efficient implementations in commercial solvers such as CPLEX or Gurobi.

We tested several alternative MILP formulations. Two of these were found to have a significant performance advantage over the others. The simplest version based on Floudas (1995) appears below. The other method relates segment indicators across time and may be more efficient for problems with more time periods.

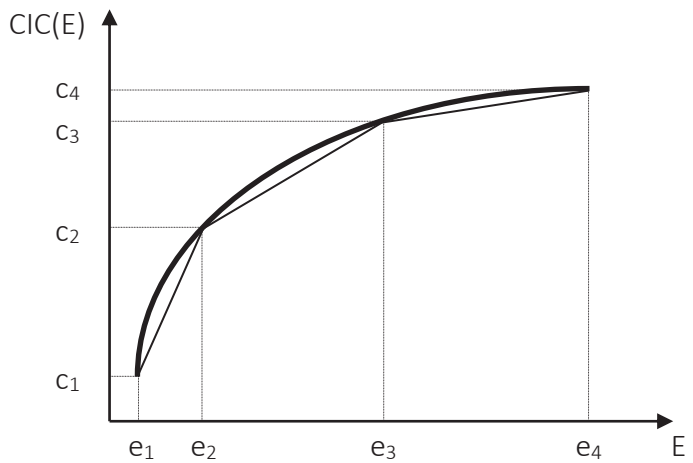

Figure 3-1. Segmentation of the experience curve.

For notational simplicity, suppose a three-segment approximation is used. Let E denote the experience variable (for a particular technology and time period, although these subscripts are omitted here) and $CIC_{lin}(E)$ the piecewise linear approximation of cumulative investment cost. Also, let e_i and c_i be the segment breakpoints as in figure 3-1. The linear segments can be written:

$$CIC_{lin}(E) = \begin{cases} a_1 + b_1 E & \text{for} \quad e_1 \leq E \leq e_2 \\ a_2 + b_2 E & \text{for} \quad e_2 \leq E \leq e_3 \\ a_3 + b_3 E & \text{for} \quad e_3 \leq E \leq e_4 \end{cases} \qquad \text{(Eq. 3)}$$

where the constants a_i and b_i are easily determined from the breakpoints e_i and c_i. Next, introduce binary variables δ_i and continuous variables X_i. The entire implementation can now be written in Greek[5]:

$$\begin{cases} CIC_{lin}(E) = (a_1\delta_1 + b_1X_1) + (a_2\delta_2 + b_2X_2) + (a_3\delta_3 + b_3X_3) \\ E = X_1 + X_2 + X_3 \\ e_1\delta_1 \leq X_1 \leq e_2\delta_1 \\ e_2\delta_2 \leq X_2 \leq e_3\delta_2 \\ e_3\delta_3 \leq X_3 \leq e_4\delta_3 \\ \delta_1 + \delta_2 + \delta_3 = 1 \\ \delta_1, \delta_2, \delta_3 \in [0,1] \end{cases} \qquad \text{(Eq. 4)}$$

or in quasi-English:

If $\delta_1 = 1$, then $\delta_2 = \delta_3 = 0$, which forces $X_2 = X_3 = 0$,
therefore $E = X_1$, then $e_1 \leq E \leq e_2$, and finally $CIC_{lin}(E) = a_1 + b_1E$.

Finding local optima

The main advantage of the piecewise linear approach is that the branch-and-bound algorithm employed by the MILP solver will eventually find and prove the global optimum. In practice though, when too many experience curves are used or the segmentation is too detailed, a very large branch-and-bound tree of binary variables can result and solution times may be prohibitive. However, the algorithm will usually find several locally optimal solutions along the way, corresponding to LP solutions to the problem with suboptimal values of integer variables. When the algorithm is terminated prematurely it will return the best known solution along with

[5] Throughout this thesis, the following notation conventions are used. Parameters (constants) begin with a lower case letter, variables begin with an upper case letter, and integer variables use a Greek (lower case) letter.

bounds on the objective value for the global optimum to the piecewise linear problem.

To find additional local optima of relevance to the energy system, we introduced temporary constraints on technology use. For example, we could direct the solver to find solutions with at least 100 GW of fuel cells. If the new solution was feasible in the original problem while the new constraint remained nonbinding (e.g. if the solution had 156 GW of fuel cells), then the new solution represented a local optimum to the original problem. In this way we get the stability and solution speed of the piecewise linear implementation while still finding the alternative locally optimal solutions that the original nonlinear implementation helped us discover.

Accuracy of the piecewise linear approximation

Due to the concavity of the cumulative investment cost curve, the optimal cost of the problem with piecewise linear curves is a lower bound to the "true" optimal cost of the original problem with continuous curves. Also, since the optimal solution to the piecewise linear problem is feasible (though not necessarily optimal) in the continuous problem (only the objective function differs), a simple post-optimization recalculation of the cost of the piecewise linear solution using continuous experience curves gives an upper bound to the continuous optimum. This provides a method of assessing the accuracy of the piecewise linear approximation: when the lower and upper bounds are very close, the approximation is adequate and it is unlikely that a refinement of the segmentation will result in a different solution.

Computational aspects

Regardless of the approach taken, it is important to remember that nonconvex minimization problems can only be solved at extreme computational expense, a fact that is only exacerbated by the high dimensionality of the problem. In our model, solution times are several orders of magnitude larger than for corresponding linear programs, and increase further with the number of experience curves and the number of time periods in the model. Therefore much effort has been placed in improving the efficiency of the implementation. Some experiences are shared here.

Williams (2013) suggests that imposing additional redundant constraints on the integer variables in MILP models may improve solution performance. We therefore added the following extra constraints on segment indicator variables, based on the observation that experience must increase over time. Here n_{seg} is the number of segments used in the approximation and $\delta_{j,t}$ denotes the binary segment indicator variable for segment j at time period t (for a certain technology, subscript omitted).

$$\sum_{j=1}^{n} \delta_{j,t} \geq \sum_{j=1}^{n} \delta_{j,t+1} \qquad \forall n: 1 \leq n \leq n_{seg} \qquad \text{(Eq. 5a)}$$

$$\sum_{j=n}^{n_{seg}} \delta_{j,t} \leq \sum_{j=n}^{n_{seg}} \delta_{j,t+1} \qquad \forall n: 1 \leq n \leq n_{seg} \qquad \text{(Eq. 5b)}$$

Significant reductions of solution time were observed after this change. This improvement can probably be attributed to a more refined (i.e. tighter) LP-relaxation[6].

Among the alternative MILP formulations, we make several attempts at introducing so-called special ordered sets (SOS) of variables. An SOS (of "type 1") is a group of variables in which exactly one variable must be non-zero, so they should be well-suited to represent segment indicators. This extra information is passed to the solver, which can adapt the branch-and-bound algorithm accordingly. However, no general performance improvement was observed in our model experiments. This somewhat surprising result may possibly be a reflection of the efficiency of the default branching procedure. The attempt to force the solver into different behavior only caused performance degradation. This could also conceivably be due to inefficient implementation of SOS branching in the CPLEX version we used, which at the time of the original implementation was CPLEX 4.0 (the latest version as of November 2019 is 12.9).

Commercial MIP solvers often have parameters that can be tweaked to improve performance for a particular problem set. We found that setting parameter `varsel` to `strong branching` reduced solution times and memory requirements by an order of magnitude. This setting activates an internal heuristic in CPLEX to determine the best variable to branch on. The heuristic is fairly time-consuming at each node, but was efficient for our problem because it reduced the number of nodes that required visiting. Also, with this parameter setting CPLEX generally converged much faster to the final solution. In other words, even the first local optimum found was very similar to the final global optimum. This was not the case with other parameter settings, as the solution could change fairly dramatically near the end.

The computational complexity of our model as measured by the amount of time, nodes and iterations required to reach the solution, was generally quite problem specific and was strongly dependent on the cost parameters used in each model

[6] The LP-relaxation is performed at every node in the branch-and-bound algorithm to determine whether the node (and its descendants) can be eliminated from further consideration.

run. The "obviousness" of the optimum is what primarily determines solution time, not problem size or number of integer variables as might be expected. In other words, a problem with several structurally different solutions but nearly identical costs could need many iterations to solve, while a problem of the same size with a clear-cut optimum would be solved relatively swiftly. For example, solution times to prove the global optimum could vary between two hours and several days for the same problem but different parameters. Similar sized linear programs were solved in a minute or two.

3.3 Discussion

We found that the piecewise linear implementation was considerably more robust than the nonlinear formulation. It consistently and relatively quickly found reasonable integer solutions, and always terminated with the global optimum for our demonstration model (though verifying the global optimum could occasionally take days as reported above).

Alternative implementations of technology learning

The computational complexity of the implementation described here grows exponentially with the number of technologies with experience curves. For this reason, very large-scale models (or even smaller models with many learning technologies) may not be reliably solved using this method. In these cases, the following alternative approaches can be explored.

One idea is to avoid optimization altogether, e.g. using approaches by e.g. Capros and Mantzos (2000), Kouvaritakis et al. (2000) and Hedenus et al. (2006), as described in the section below. In market simulation models, using endogenous nonlinear feedback relations such as experience curves to describe cost dynamics is no more computationally difficult than using exogenous assumptions. These models are particularly appropriate for answering "what if"-type questions, especially in the context of evaluating technology support schemes. However, they are less suitable for finding efficient energy solutions for society as a whole, as this would require extensive manual search by the model user.

A frequently observed result in optimization models with endogenous learning is that the model tends to either invest maximally in emerging technologies (i.e. up to the growth constraint) from the first time period onwards, or to neglect the technology altogether. This observation naturally suggests a simplification of the implementation. Specify an exogenous "time-table" for fast growth in an emerging technology, and calculate the resulting costs exogenously using an experience curve. After some decades the technology can be regarded as having reached maturity,

with slowly decreasing exogenous costs over time. This approach would lead to a greatly simplified MIP implementation, with only one binary variable per learning technology. If the model chooses to invest in a technology at all, it would be constrained to invest according to the time-table during the initial decades (and be unconstrained thereafter). If not, experience is set to zero for all time periods. We simply use two constraints of the form:

$$E_{k,t} = \delta_k e_{k,t} \quad \forall t: t \leq t_{\text{mature}} \qquad \text{(Eq. 6a)}$$

$$E_{k,t} \leq \delta_k e_k^{\max} \quad \forall t: t > t_{\text{mature}} \qquad \text{(Eq. 6b)}$$

Here $E_{k,t}$ is the variable representing cumulative experience of technology k at time t, δ_k the binary indicator variable for whether or not investments in that technology take place, $e_{k,t}$ the exogenous cumulative experience parameter following a time-table with fast growth, and $e_k^{\max}$ a suitable large value that cumulative experience cannot exceed. The objective function would then be entirely linear, with terms of the form $C(e_{k,t}) \cdot I_{k,t}$.

The drawback of this approach is the lack of flexibility in the initial investment time-table. This has negligible impact on system costs when capacities are very small, but can become significant later.

One of the main problems with models with exogenous technology costs is that resulting technology investment trajectories are often incompatible with the cost assumptions – the output is inconsistent with the input. A common example is when investments in swiftly improving technologies only occur in later time periods once costs have been reduced, despite the fact that these cost reductions could not take place without significant investments. This particular problem can be addressed by using experience curves exogenously to generate the cost input (based on assumptions of future capacity), and recalculating the cost input based on feedback of resulting capacity output. Model runs are iterated in this way until they converge upon a stable solution, which then becomes internally consistent. During my time at the IEA, I would run the global Energy Technology Perspectives model in this way (IEA, 2008, 2006). The model would usually approximately converge after 3-10 iterations. However, there is no guarantee of convergence. If oscillations develop, some manual tweaking may be required (e.g. by introducing minimum or maximum constraints to a technology). A significant shortcoming of this approach is that the model has no foresight of technology development, so the final converged result represents at best a locally optimal solution, and possibly only a feasible solution (see section 5.5 for thoughts about a similar soft-linking approach).

The significance of the global optimum

Given the large uncertainties in virtually all techno-economic parameters that represent the current system, and even larger uncertainties for parameters that represent the future, it is relevant to ask: what is the significance of the global optimum in models? Does it have any inherent meaning or does all meaning drown in parameter uncertainty?

In my experience, modelers too often focus on the optimal solution. Cost minimization can simply be viewed as a filter that produces a single solution out of a multitude of other feasible solutions, albeit one with interesting economic properties.

The problem of parameter uncertainty can be mitigated by sensitivity analyses on critical parameters. However, sensitivity analysis is frequently used only to determine what other solutions can become optimal when parameters are varied, and not to explore marginally suboptimal solutions. Ideally any model study based on cost minimization should also explore if there are fundamentally different solutions marginally higher cost. The search for other interesting solutions could be automated within the existing optimization framework (e.g. by adding a cost constraint and changing the objective to maximize the distance to previously found solutions), and could provide much new insight about the systems studied.

This idea has recently been formalized and gaining traction under the term "modeling to generate alternatives" (MGA). For some recent studies using MGA in an energy system context, see (DeCarolis, 2011; DeCarolis et al., 2016; Price and Keppo, 2017).

In this context, models with endogenous experience curves have two advantages over models with exogenous technological development. First, the assumptions made about cost dynamics become more explicit and quantifiable, which highlights the need for sensitivity analysis and facilitates MGA. Second, the potential for multiple locally optimal solutions already encourages exploration of the solution space.

3.4 Legacy

The following is a review of the literature on using endogenous technological learning (ETL) in energy models. Normally this section would be called "Background" and would appear first in the chapter, but that approach would feel awkward since the first published papers of the field were our paper 1 and Messner (1997), a similar ETL implementation developed independently of our work.

An early attempt to use ETL with experience curves within an energy systems modeling framework was reported in Anderson and Bird (1992). They use a simulation

model to study the costs of a global transition to a renewable energy system. Renewable energy costs are determined endogenously by experience curves, but market penetration of technologies is specified exogenously; strategic choices of technological trajectories are thus left to the model user.

The MESSAGE linear programming model was extended to include endogenous experience curves by Messner (1997). The study focused on a comparison of results using static (constant) costs, dynamic (exogenous) costs, and learning (endogenous) costs. ETL was implemented using a piecewise linear formulation of experience curves and solved using special ordered sets in a reduced single-region version of the full 11-region MESSAGE model, in which demand-side technologies were removed. It is unclear from the paper whether the model solved to the global optimum or terminated at a "best known" solution, and there is no mention of the possibility of multiple local optima.

The ETL formulation presented in this chapter (and originally in my licentiate thesis) was implemented in the widely used MARKAL model by Ad Seebregts at ECN in the Netherlands and Leonardo Barreto at PSI in Switzerland (Barreto and Kypreos, 1999; Seebregts et al., 1998a) and was subsequently included in the standard MARKAL distribution (Loulou et al., 2004). Barreto documented the approach extensively in his PhD thesis (Barreto, 2001, pp 41-49), and it eventually became the standard citation for the mathematical formulation of ETL within the MARKAL community.

Seebregts (1998b) was the first to demonstrate feasibility of the ETL approach in a large-scale optimization model. He used the MARKAL-Europe model with 510 technologies and 10 technologies with ETL, and concluded that the increase in solution time when ETL is enabled “remains acceptable”. Seebregts et al. (2000) introduce technology clustering, where technologies are grouped into clusters and their cost development are linked to five key learning technologies. This approach facilitates analysis of learning crossover (between technologies) and spillover (between regions).

The TIMES model (Loulou et al., 2005) is essentially a more flexible version of the MARKAL model and has directly adapted parts of the MARKAL code base, including the ETL implementation. A recent example of ETL modeling with TIMES is Anandarajah (2015), which uses the 16-region TIAM-UCL integrated assessment model based on the TIMES framework to study technological learning in the transport sector. Its approach is similar to that of Seebregts et al. (2000), with three key technology clusters which are the basis for many individual learning technologies.

Kypreos (2003) introduced ETL in the MERGE model using an unusual two-model approach. A global MERGE model with a simplified energy system representation was iteratively soft-linked with a more detailed multiregion bottom-up model. ETL was introduced in both submodels. The original nonlinear experience curve equation was used in the nonlinear MERGE model and piecewise linearization in the technology-rich model.

Hedenus et al. (2006) use quasi-endogenous learning with a limited foresight mechanism in the GET model, a dynamic global multisector energy system model. Investment decisions in each time period are made with 30 years of foresight, but with no foresight of learning. Technology costs are reduced between time periods using experience curves, and new decisions are made in the next time period based on the lower costs. This myopic approach evades the computational difficulties of ETL but essentially implies that the underlying optimization model is used as an energy market simulation model.

Capros and Mantzos (2000) adopt a similar "dynamic but myopic" approach to study induced technical change of demand-side technologies in the PRIMES model, a bottom-up partial equilibrium model based on linked modules that simulate energy markets.

Kouvaritakis et al. (2000) develop a module that implements two-factor learning for energy market simulation models such as the POLES model. They use an agent-based approach with large energy suppliers as the decision-making agents. Two-factor learning means that cost decreases by both learning-by-doing and learning-by-research. de Feber et al. (2003) discuss two-factor learning in the context of large energy system optimization models. They note that the learning-by-research term in two-factor learning prohibits the use of MILP approximations, which makes the approach intractable for large models.

Bauer et al. (2012) describe the REMIND-R model, an energy-economy-environment (E3) model that includes ETL for energy technologies. Since nonlinear equations are already used in the hard-linked economy submodel, a straightforward nonlinear implementation of ETL can also be used (Bauer et al., 2017). The authors do not relate whether or not the nonlinearities cause difficulties solving the model.

A recent ETL implementation is used by Heuberger et al. (2017), who present a custom power capacity expansion model of the UK called ESO-XEL. The model is dynamic with 5-year periods but nevertheless can be run with full hourly time resolution (8760 hours), or alternatively using reduced time representation by data clustering. There are 15 electricity generation technologies with learning in the model, which uses a piecewise linear ETL implementation attributed to Barreto (2001).

4 Uncertain learning (paper 2)

4.1 Background

Any study based on experience curves is highly sensitive to uncertainty in the learning rates of the underlying technologies[7]. Even relatively small numerical differences in learning rates may cause dramatically divergent cost trajectories, due to the exponential relationship. When experience curves are used to describe technology cost development in energy system models, it is likely that learning rate uncertainty is the most significant parameter uncertainty in the model.

Research questions

Can stochastic programming be used to consider learning rate uncertainty endogenously in energy models? How can the standard stochastic programming method be adapted for this? Does a combined model at demonstration scale generate qualitatively new insights?

Stochastic programming

When an energy system model is subjected to a limited number of critical parameter uncertainties, an optimal solution that considers the uncertainty endogenously

[7] Initial technology costs and experience (parameters c_0 and e_0 in equation 1) also have a large effect on results, but they since they represent a starting condition they can be measured, at least in principle. In practice however, this can be quite difficult. Costs of non-commercial emerging technologies may be highly speculative. Additionally, the initial experience parameter of a technology should probably also consider spillover experience from related technologies (e.g. stationary gas turbines and jet engines, solar PV modules and other semiconductor manufacturing, wind turbines and aviation aerodynamics), which is problematic to quantify.

can be found using stochastic programming. For example, suppose that an integrated assessment model needs to consider three possible values for the climate sensitivity (high, mid, and low), which can be assigned probabilities a priori. The uncertainty is further assumed to be completely resolved in some future year, say in 2050. This is conceptually illustrated in figure 4-1. In the first few time periods of the model, all variables follow a single pathway that hedges against the possible future outcomes of the climate sensitivity. After the uncertainty is eliminated, the model adapts to the reality of each of these parallel timelines, resulting in three different investment pathways.

The previous paragraph describes a two-stage stochastic programming problem. If the uncertainty needs to be resolved progressively, the tree in figure 4-1 can be extended with additional branches, which creates a multi-stage problem. Or alternatively, multi-stage problems may arise when uncertainties of several parameters are considered simultaneously.

A straightforward implementation of stochastic programming involves adding an additional dimension to every variable of a standard deterministic model, i.e. subscripting the variables by scenario/outcome. Then constraints are added to equalize variable values in parallel branches before the time period when uncertainty is resolved. The new objective function is a linear combination of the total costs of each branch, weighted by their probabilities. The resulting problem remains a linear program (assuming the original deterministic problem was linear) with n times the number of variables, with n being the number of leaves in the scenario tree.

The stochastic model can be solved using a standard LP solver. Alternatively, more efficient solution algorithms may involve decompositioning techniques that take advantage of the particular block structure of stochastic programming problems. However, convergence speed with decompositioning is sometimes slow, and just solving the large LP using a modern interior-point solver may be faster or more reliable despite its theoretical inefficiency. In paper 2 this brute-force method was chosen, primarily for its simplicity.

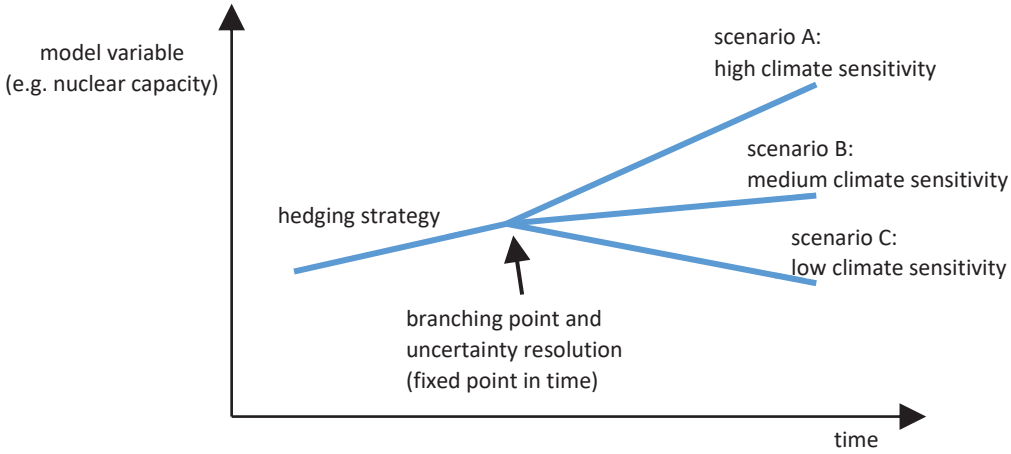

Figure 4-1. Conceptual sketch of standard stochastic programming.

4.2 Method

Experience curves with uncertain learning

For uncertainty in the learning rate of experience curves, resolving uncertainty at a fixed point of time would be inappropriate. Learning-by-doing implies that cost reductions only take place with increasing experience. Similarly, it is reasonable that *information* about the ongoing rate of cost reductions should only be acquired with experience. To capture this dynamic in the GENIE test model, learning rate uncertainties are assumed to resolve once a threshold level of cumulative installed capacity is reached.

The experience curve uncertainty is illustrated in figure 4-2. Although six technologies in the model have costs based on experience curves, only solar PV and fuel cells have experience curves with uncertain learning rates. Solar PV is assumed to develop along the established 20% learning rate until 5 GW of experience is reached[8], after which it either continues to follow this "high learning" branch or breaks off on a "low learning" path with a 10% learning rate. Since there was no established learning rate for fuel cells when the model was implemented, the paths for fuel cells diverge immediately from the starting capacity, with assumed learning rates of 15% (high) and 8% (low). The uncertainty resolution threshold is 50 GW for both technologies, which implies that the model does not "know" which branch it is following – and therefore cannot adapt the energy system – until this information threshold is reached.

[8] The first time period of this version of the GENIE model represents the year 2000, at which time only 750 MW of solar PV capacity had been installed globally.

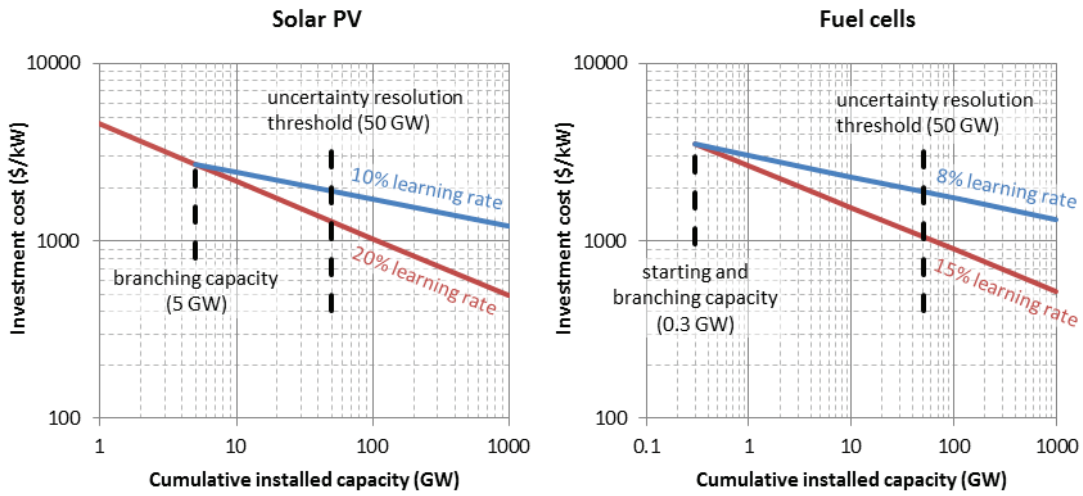

Figure 4-2. Stochastic experience curves.

Mathematical description

The resulting model can be represented using a mixed-integer linear program as follows. Introduce binary threshold indicators $\gamma^s_{k,t}$ to represent whether or not the experience variable $E^s_{k,t}$ has reached the threshold experience levels $e^{\text{threshold}}_{\text{k}}$ for technology k at time t in scenario branch s. Here k is indexed only over the set of technologies with uncertain experience curves (i.e. solar PV and fuel cells), not all technologies.

$$\forall s, t: \begin{cases} E^s_{\text{PV},t} \leq e^{\text{threshold}}_{\text{PV}} + e^{\max}_{\text{PV}}\, \gamma^s_{\text{PV},t} \\ E^s_{\text{PV},t} \geq e^{\text{threshold}}_{\text{PV}}\, \gamma^s_{\text{PV},t} \end{cases} \qquad \text{(Eq. 7a)}$$

$$\forall k, t: \begin{cases} E^{\text{PV low, FC high}}_{k,t} \leq E^{\text{PV high, FC high}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV high, FC high}}_{\text{PV},t} \\ E^{\text{PV high, FC high}}_{k,t} \leq E^{\text{PV low, FC high}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV high, FC high}}_{\text{PV},t} \end{cases} \qquad \text{(Eq. 7b)}$$

$$\forall k, t: \begin{cases} E^{\text{PV low, FC high}}_{k,t} \leq E^{\text{PV high, FC high}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV low, FC high}}_{\text{PV},t} \\ E^{\text{PV high, FC high}}_{k,t} \leq E^{\text{PV low, FC high}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV low, FC high}}_{\text{PV},t} \end{cases} \qquad \text{(Eq. 7c)}$$

$$\forall k, t: \begin{cases} E^{\text{PV high, FC low}}_{k,t} \leq E^{\text{PV low, FC low}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV high, FC low}}_{\text{PV},t} \\ E^{\text{PV low, FC low}}_{k,t} \leq E^{\text{PV high, FC low}}_{k,t} + e^{\max}_{\text{PV}}\, \gamma^{\text{PV high, FC low}}_{\text{PV},t} \end{cases} \qquad \text{(Eq. 7d)}$$

$$\forall k,t: \begin{cases} E_{k,t}^{\text{PV high, FC low}} \leq E_{k,t}^{\text{PV low, FC low}} + e_{\text{PV}}^{\max}\, \gamma_{\text{PV},t}^{\text{PV low, FC low}} \\ E_{k,t}^{\text{PV low, FC low}} \leq E_{k,t}^{\text{PV high, FC low}} + e_{\text{PV}}^{\max}\, \gamma_{\text{PV},t}^{\text{PV low, FC low}} \end{cases} \qquad \text{(Eq. 7e)}$$

For brevity, only equations for $\gamma_{\text{PV},t}^{s}$ are shown. Analogous equations for $\gamma_{\text{FC},t}^{s}$ are also required but are not shown here. Equation 7a links the binary indicator variable $\gamma_{k,t}^{s}$ to the threshold experience levels $e_{k}^{\text{threshold}}$. The parameter $e_{k}^{\max}$ is an arbitrary large value that cumulative experience cannot exceed during the time period under study (c.f equation 6 in section 3.3). Equations 7b-7e then force different scenario branches to remain identical as long as threshold experience levels have not yet been reached ($\gamma_{k,t}^{s} = 0$), but relax this constraint once threshold experience levels are attained ($\gamma_{k,t}^{s} = 1$).

The reason why $\gamma_{k,t}^{s}$ needs to be indexed over the scenario branches s may not be immediately apparent, but the decision about whether or not to invest up to threshold experience levels for a certain technology may depend on how fast another technology with uncertain learning is developing. The interacting technologies could conceivably be either substitutes (so one becomes less interesting if the other achieves its full learning potential) or complementary (synergies make a technology even more appealing if another succeeds).

In equations 7a-7e above, every occurrence of $E_{k,t}^{s}$ can be replaced by $X_{k,t,p}^{s}$ (for all p in the set of piecewise linear segments, see equation 4). This is functionally equivalent but increases the number of constraints and reduces solution times. This alternative formulation is in fact the one used in GENIE.

Objective: probability-weighted cost or minimize maximum regret

The default objective function of the stochastic problem is simply the weighted sum of discounted system costs C_s for each scenario branch, using the probability of each branch as weights (equation 8). However, it can be difficult to assign probabilities to each branch a priori.

$$\min \sum_{s} p_s C_s \qquad \text{(Eq. 8)}$$

Alternatively, the stochastic programming problem can be solved without assigning probabilities to the branches by minimizing the "maximum regret" as follows (e.g. Loulou and Kanudia, 1999). First, find ideal costs for each branch c_s^{ideal} by optimizing the deterministic problem assuming learning rates are known from the beginning. Then, in any given strategy (i.e. a proposed feasible solution to the stochastic problem), the "regret" can be calculated for each scenario branch (or outcome) as the difference between the system costs of the strategy (after adaptation to that

branch) and the ideal system costs of that branch. The maximum regret for a strategy is the highest value of the regret over all branches. Finally, strategies can be chosen by solving the uncertain problem while minimizing the maximum regret.

This can be implemented as a linear programming problem by adding one continuous variable for the maximum regret $R^{\max}$, and one constraint for each scenario branch that forces $R^{\max}$ to be greater than the regret of each individual branch. The objective is simply to minimize the maximum regret (equation 9a-b).

$$\min R^{\max} \qquad \text{(Eq. 9a)}$$

$$R^{\max} \geq C_s - c_s^{\text{ideal}} \qquad \forall s \qquad \text{(Eq. 9b)}$$

In paper 2, the optimal hedging strategy was determined using expected costs (equation 8). Maximum regret was only calculated exogenously for a number of strategies; optimization using equation 9 was not used.

4.3 Results

The approach presented above introduces the model dynamic that information on learning rate uncertainty can only be obtained by undertaking investments in energy markets.

Unsurprisingly, model results are strongly dependent on the probabilities of the high or low learning branches for solar PV and fuel cells. Paper 2 initially investigates the optimal hedging strategy for the "50-50" case in which both branches are equally probable for both technologies.

The optimal hedging strategy for the 50-50 case involved making immediate investments in fuels cells at the maximum allowed growth rate in the model. This allowed fuel cells to reach the information threshold capacity level by the year 2020. Early investments in solar PV also took place, but these were somewhat delayed and only reached the threshold in 2030 (figure 4-3). After threshold capacity levels were reached, the model adapted investments to the learning rates of each branch, eventually resulting in four completely different energy system outcomes (figure 4-4).

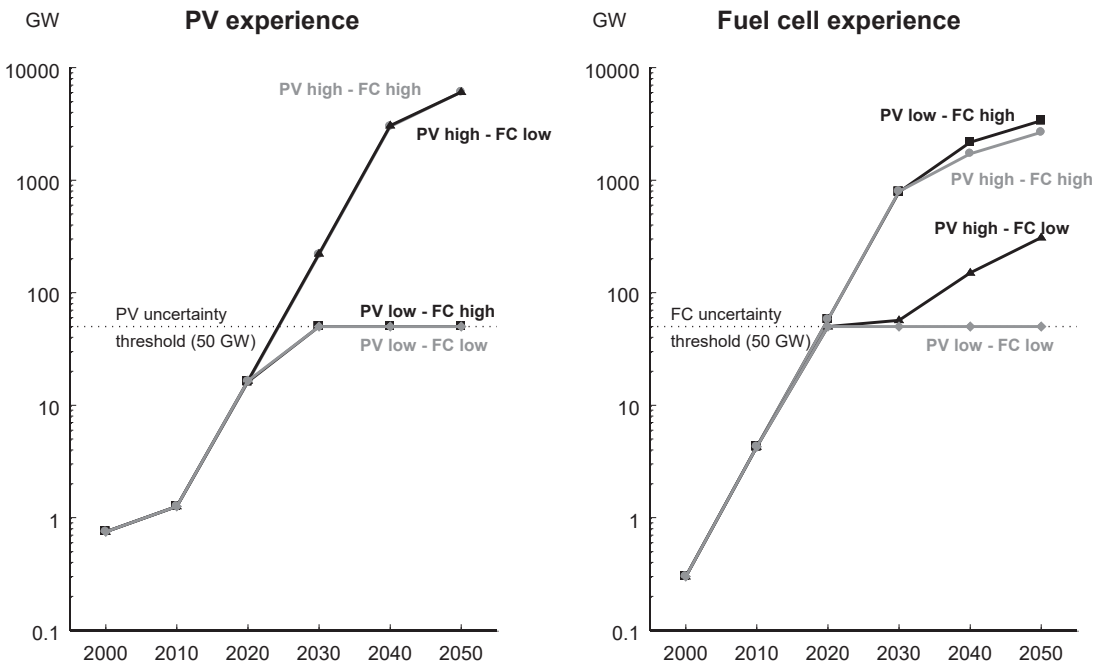

Figure 4-3. Growth of emerging technologies in the optimal hedging strategy.

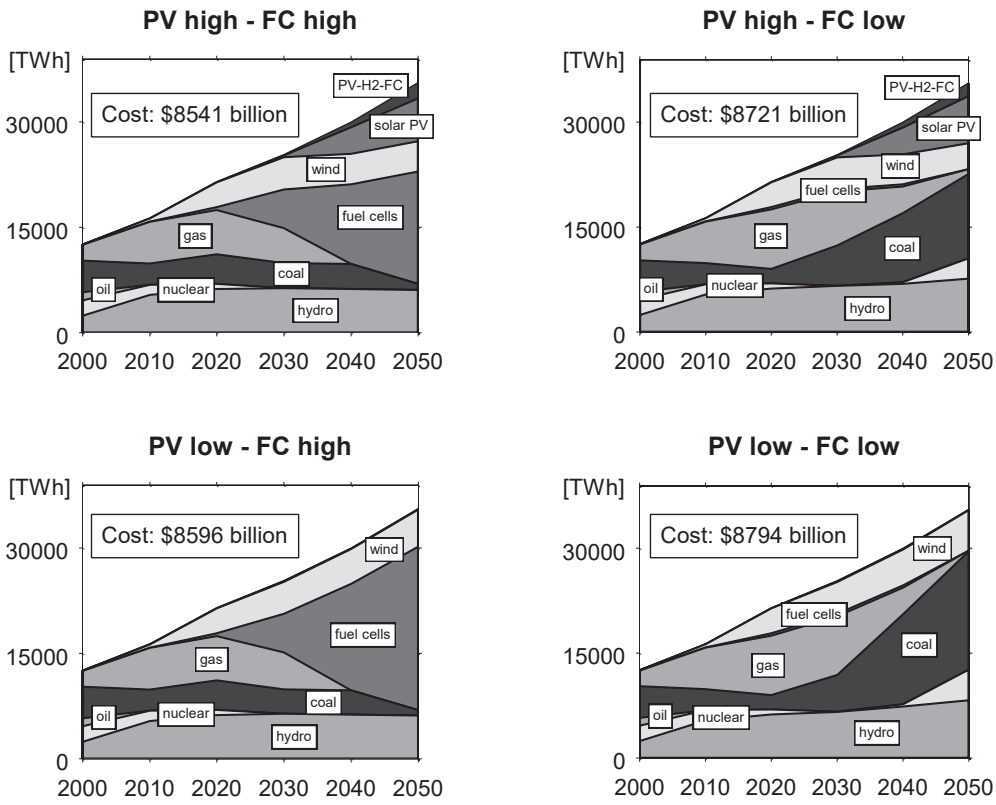

Figure 4-4. The four possible outcomes of the optimal hedging strategy.

Additionally, four different strategies were constructed (one for each branch) using optimal initial investment paths as if learning rates were known from the beginning, then each strategy was subjected to all four actual learning outcomes. This meant that strategies that assumed low learning rates did not reach threshold capacity levels and therefore never learned of foregone opportunities for high learning. When low fuel cell learning was assumed, potentially low cost systems were missed. The system cost difference was relatively insignificant when low solar PV learning was assumed, but in that case systems with significantly lower CO_2 emissions were missed. All investments and all choices have opportunity costs; choosing not to make learning investments in emerging technologies may have the opportunity cost of ending up with a more costly energy system, or one with higher emissions.

Finally, a sensitivity analysis was performed in which the probabilities of high learning were varied from 1% to 99% for both solar PV and fuel cells, and the optimal hedging strategy was calculated for each probability combination. We found that even a 10% probability of high learning rates for fuel cells was sufficient to motivate immediate investments at the maximum allowed rate (figure 4-5). Solar PV required approximately a 75% probability of high learning for immediate investments, or 50% probability for slightly delayed investments (10 years). However, this relative unfavorability of PV may be an artifact of the intermittency constraint in the model, which limits the combined contribution of wind and PV electricity to 30% of annual electricity demand.

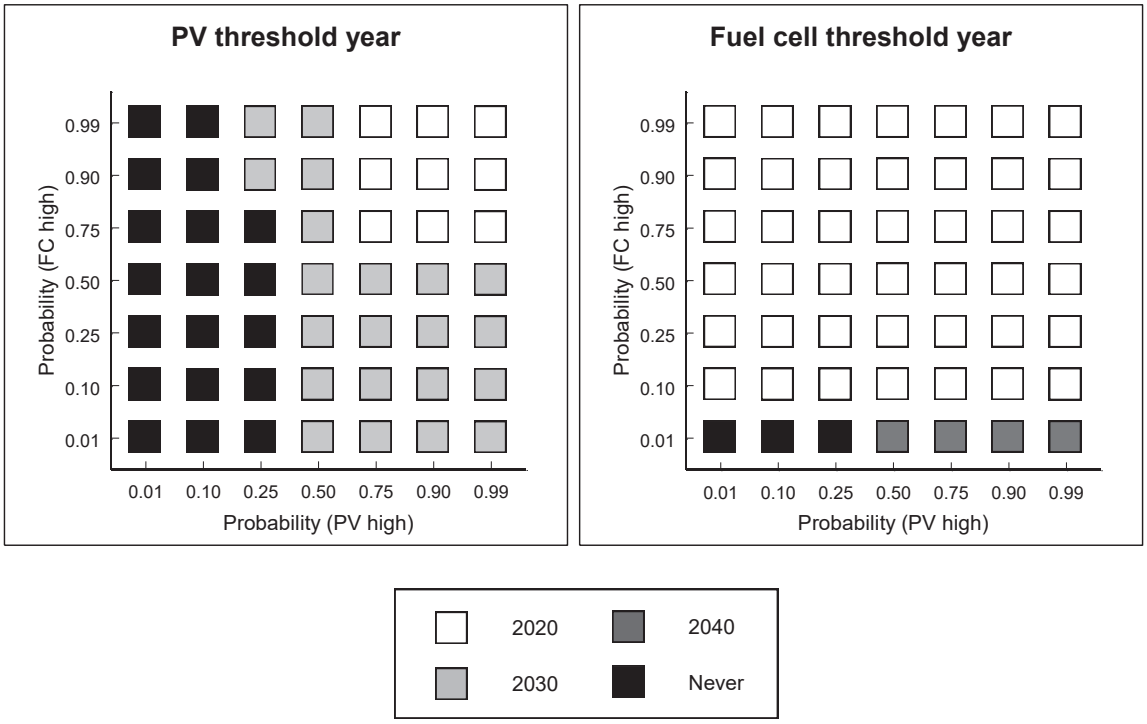

Figure 4-5. Summary of 49 model runs varying probabilities of high learning.

5 Reaching temperature targets with BECCS (paper 3)

5.1 Background

This chapter discusses paper 3, a study of the role of bioenergy with carbon capture and storage (BECCS) for meeting global temperature targets, particularly the 1.5°C and 2°C targets. Earlier working titles include "Reversing global warming" and "The economics of BECCS", which are apt descriptions of additional themes discussed in the paper.

Bioenergy can be carbon neutral when its combustion emissions are balanced by the carbon that was absorbed from the atmosphere as the biomass grew. This is the case when the entire biomass production chain is sustainable; i.e. no fossil energy use, no land use change or soil carbon imbalances, and biomass is replanted after harvest. When carbon neutral or low-carbon bioenergy is combined with carbon capture and storage, negative emissions can occur. BECCS is not the only negative emission technology (NET), but it unique because it can deliver useful energy while removing CO_2 from the atmosphere. Evidence is mounting that BECCS and other NETs are of critical importance if ambitious climate targets are to be achieved (Fuss et al., 2018; IPCC, 2018). Here we focus on BECCS; other NETs are discussed below.

In the 1990s and 2000s, targets for responding to the threat of climate change were commonly expressed as stabilization targets for atmospheric CO_2 concentration, and were typically in the range 350-550 ppm depending on the ambition level of emission reductions. One of the first studies that assessed the potential contribution of BECCS for meeting concentration targets was Azar et al. (2006), which along with three similar studies by other research groups became the basis for the discussion of negative emissions in the IPCC Fourth Assessment Report (IPCC 2007, Minx et al., 2018).

Azar et al. (2006) used the GET multisector global energy model to estimate how costs of meeting various levels of CO_2 concentration targets were affected by the availability of carbon capture and storage (CCS) of fossil fuels and of BECCS. They found that BECCS only marginally reduced the cost of meeting a 450 ppm target (cost reduction < 10%), but the cost of meeting a stricter 350 ppm target was reduced by 40-60%. Azar et al. (2010) largely confirmed these results in a three-model intercomparison, and additionally mapped the limits of which targets were achievable in the models. In all three models, considerably lower levels of CO_2 concentration could be reached when BECCS was available.

In 2011, my colleagues and I initiated a project to revisit these earlier studies using a newer version of the GET model, which had since been updated with improved representations of heat and transport sectors. The idea was to combine GET with an in-house simple climate model (Johansson, 2011) and reevaluate the role of BECCS, now using global temperature targets instead of concentration targets.

5.2 Research questions

Do the conclusions of the studies based on concentration targets still hold for temperature targets, or would the heat inertia of the oceans limit the potential benefit of BECCS for temperature targets? If we fail to meet a given temperature target in the future but are willing to accept a temporary overshoot of the target, can BECCS be used to reduce global temperatures and meet targets retroactively? If so, to what extent can BECCS also be used to roll back global warming at a larger scale? How important is the type of target used (i.e. whether or not we allow temperature overshoot) for the value of BECCS? Finally, how are answers to these questions affected by uncertainty about climate sensitivity, global availability of biomass and carbon storage potential?

5.3 Method

We extended the single region version of the GET multisector global energy system model that has been progressively developed at the division of Physical Resource Theory since its original formulation in Azar et al. (2003). We rewrote the climate model initially developed in Johansson (2011) to a representation suitable for hard-linking with GET, and updated the carbon cycle to use nonlinear impulse response functions describing CO_2 uptake by the oceans and terrestrial biosphere. Concentrations of methane and nitrous oxide are tracked endogenously, with energy-related emissions produced by the GET module and non-energy emissions represented by an exogenous baseline along with potential emission reductions using

marginal abatement cost (MAC) curves. Radiative forcing of greenhouse gas concentrations is based on nonlinear parameterizations from IPCC reports (IPCC 2001, IPCC 2007), and radiative forcing of aerosols is calibrated by scaling its contribution to match the historical temperature record for the given climate sensitivity input. Annual temperatures are calculated from total annual radiative forcing using an upwelling-diffusion energy balance model with polar overturning.

The resulting hard-linked energy-climate model is called GET-Climate. It is written in GAMS and solved using CONOPT 4. A graphical representation of flows and internal feedbacks of the climate module and interactions with the energy module is shown in figure 5-1. For more information on the model formulation, see the appendix of paper 3.

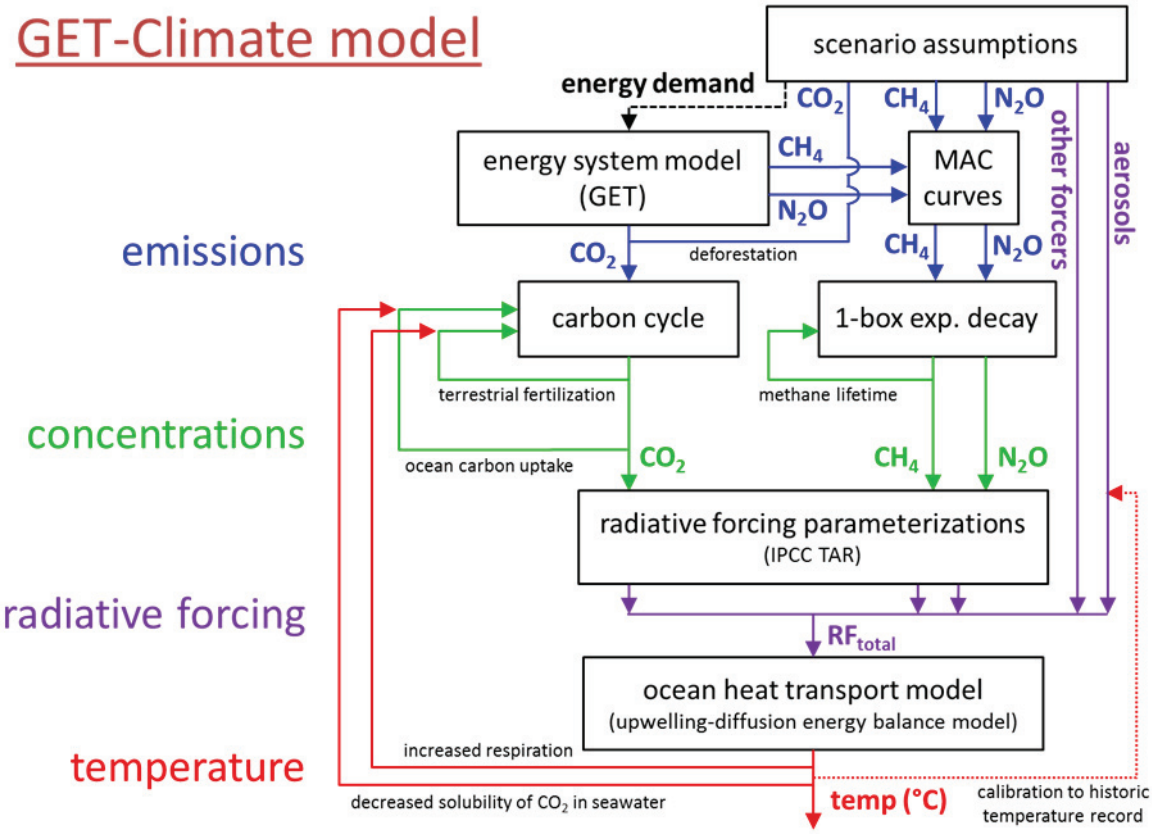

Figure 5-1. Schematic overview of the climate module, its feedbacks and interactions with the energy system module.

The climate module contains multiple nonlinearities and feedbacks that increase its computational complexity. The combined GET-Climate model is therefore also nonlinear, despite the linear equations of the energy module. The nonlinearities and the relatively large size of the embedded energy module[9] cause considerable numerical difficulties when solving the model, particularly since nonlinear solvers generally not suited for problems with many variables and constraints. A number of modeling "tricks" were therefore employed to help the nonlinear solver reliably find solutions. To help the solver start from feasible initial variable values, we pre-solved the energy model with a linear solver and ambitious concentration targets and spinned up the climate module based on the energy system result. We also introduced (mostly redundant) bounds on climate model variables.

GET-Climate generates least-cost technology investment pathways for the global energy system during 2010-2150 with perfect foresight, for a given energy demand scenario and temperature target. Two types of temperature limits are considered: a "ceiling target" which may never be exceeded, and an "overshoot target" which is only enforced in the year 2150 and therefore allows for a temporary overshoot of the temperature response.

The energy system module based on GET contains several variants of BECCS technology for different energy sectors, including condensing power and cogeneration plants in the electricity sector, large-scale heat production in district heating and industrial sectors, and liquid fuel production for use in the transport sector.

5.4 Results

In figure 5-2, we present pathways for CO_2 emissions, atmospheric concentration, and temperature for meeting 1.5°C and 2°C targets of both ceiling and overshoot type. Generally, we note that overshoot pathways with BECCS feature higher emissions in the near term but global net-negative emissions in the distant future. The same tendency is found in ceiling emission pathways, but to a much lesser extent. Also, ceiling pathways do not become net-negative.

Figure 5-3 presents scenario abatement costs (i.e. the difference between the system cost of a model run under a target and a business-as-usual run with no target) obtained while varying the target level. We observe that BECCS significantly reduces costs of overshoot targets, but has little effect on ceiling targets. Also, when BECCS

[9] Note that the box representing the energy module in figure 6-1 is disproportionately small. The number of model equations in the energy system and climate modules are roughly equal. In terms of number of generated equations, the energy module is much larger than the climate module.

is available, substantially lower overshoot targets become feasible – even targets below 1°C (in the long run, and at high cost).

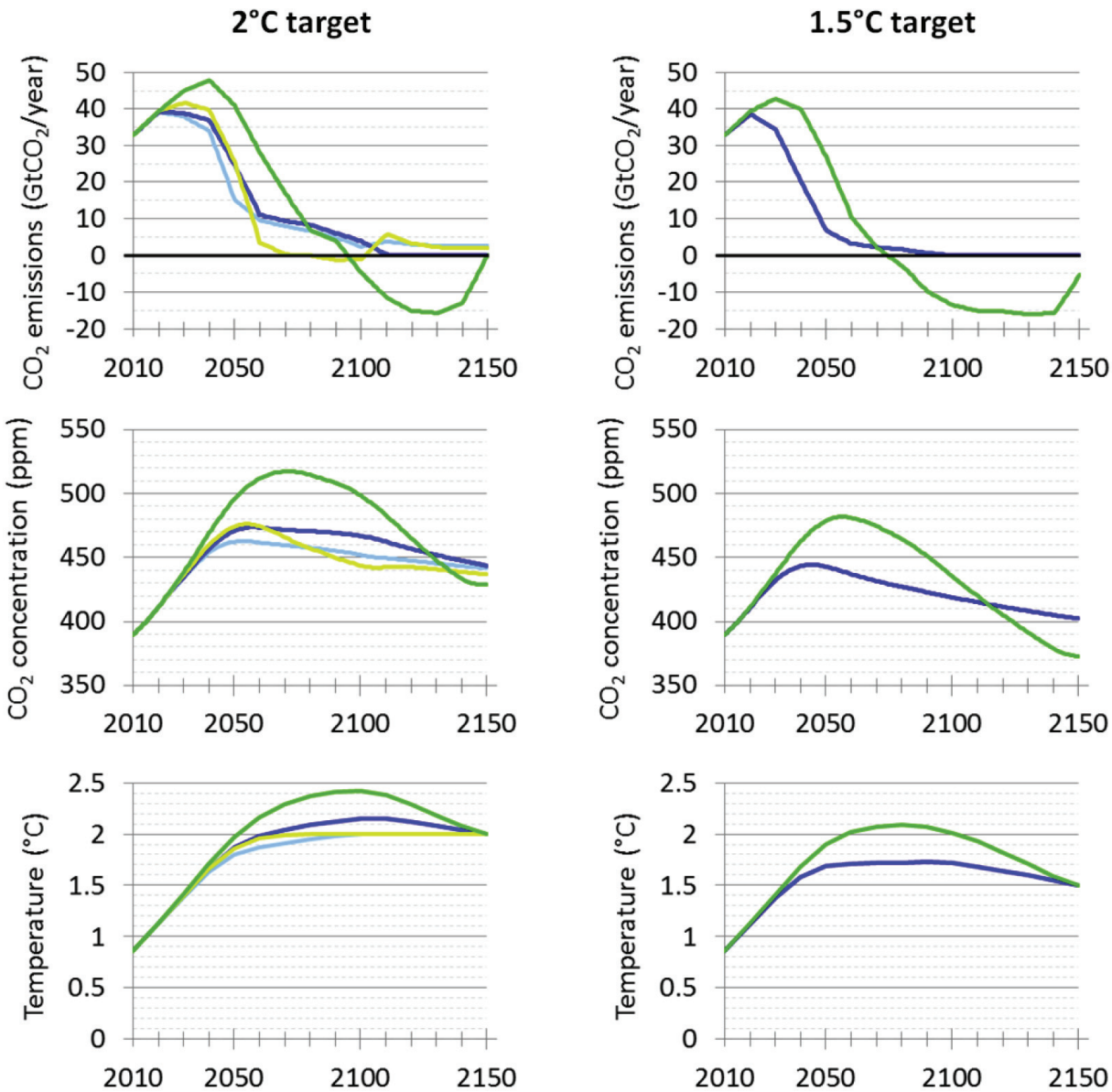

Figure 5-2. **CO_2 emissions, CO_2 concentration and mean surface temperature increase, for 2°C targets (left) and 1.5°C targets (right).** Cases shown are: fossil CCS with ceiling targets (light blue), fossil CCS with overshoot targets (dark blue), fossil CCS and BECCS with ceiling targets (light green) and fossil CCS and BECCS with overshoot targets (dark green). Ceiling cases for the 1.5°C target are infeasible in our model.

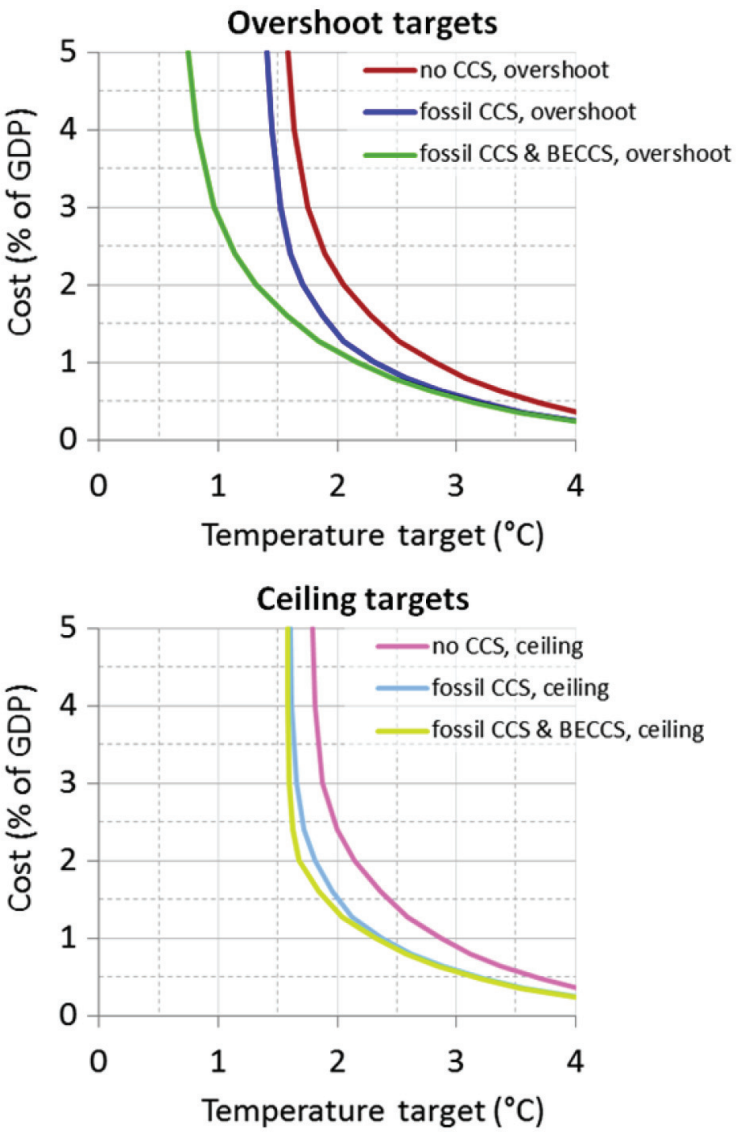

Figure 5-3. **The value of BECCS with overshoot targets (top) and ceiling targets (bottom)**. Abatement costs in percent of discounted future GDP as a function of temperature target for multiple model runs. Cases shown are: no CCS with overshoot targets (dark red), fossil CCS with overshoot targets (dark blue), fossil CCS and BECCS with overshoot targets (dark green), no CCS with ceiling targets (light red), fossil CCS with ceiling targets (light blue) and fossil CCS and BECCS with ceiling targets (light green).

Figure 5-4 shows emission pathways for the 2°C ceiling target and the 1.5°C overshoot target in the same chart, to illustrate that they (coincidentally) are nearly identical until 2080. However, the underlying development of primary energy supply are different in the two scenarios. Considerably less fossil CCS is used in the 1.5°C overshoot case than in the 2°C ceiling case, because the model chooses to reserve carbon storage capacity for BECCS and net-negative emissions. Nevertheless, this suggests that the result from Meinshausen et al. (2009), that reachable temperature targets are largely determined by cumulative emissions up to 2050, does not hold in the general case when NETs are available and overshoot is allowed. It also illustrates that the ambitious 1.5°C target may be reachable even after "a slow start", but that this would involve temperature peaking at 2°C before it declines back to the target level.

We also discuss results from the sensitivity analysis of main numerical assumptions presented in the supplementary material. For example, we find that the cost benefit of BECCS is even higher than in the default case in scenarios with higher climate sensitivity (supplementary figure 3). We also note that if the available amount of biomass is reduced from 200 to 100 EJ/year, then the benefit of BECCS is greatly reduced. In this case, net-negative emissions are only 5-6 Gton CO_2/year, roughly a third of the level[10] that is reached with our default assumptions (supplementary figures 4 and 6).

We conclude that there are two fundamentally different mechanisms by which BECCS and other NETs can provide economic benefit. First, they can compensate for emissions in sectors which may lack low-cost mitigation options or for emissions in countries that do not participate in international climate agreements. In this way BECCS can be seen as a backstop mitigation technology; its existence provides an upper bound to mitigation costs. However, BECCS is not a particularly low-cost option abatement technology in itself.

The second mechanism is more apparent in our paper. BECCS and other NETs allow emission reduction efforts to be postponed, which is economically advantageous when future costs are discounted. We find that this time-shifting effect is more significant for overshoot targets than for ceiling targets, simply because there is little headroom to postpone emission reductions in the case of ceiling targets. Both flexibility mechanisms are also discussed in Lomax et al. (2015), under the terms "decoupling in space" and "decoupling in time".

[10] The total amount of negative emissions is likely halved along with the biomass availability, but some of the negative emissions are used to compensate for emissions in other sectors.

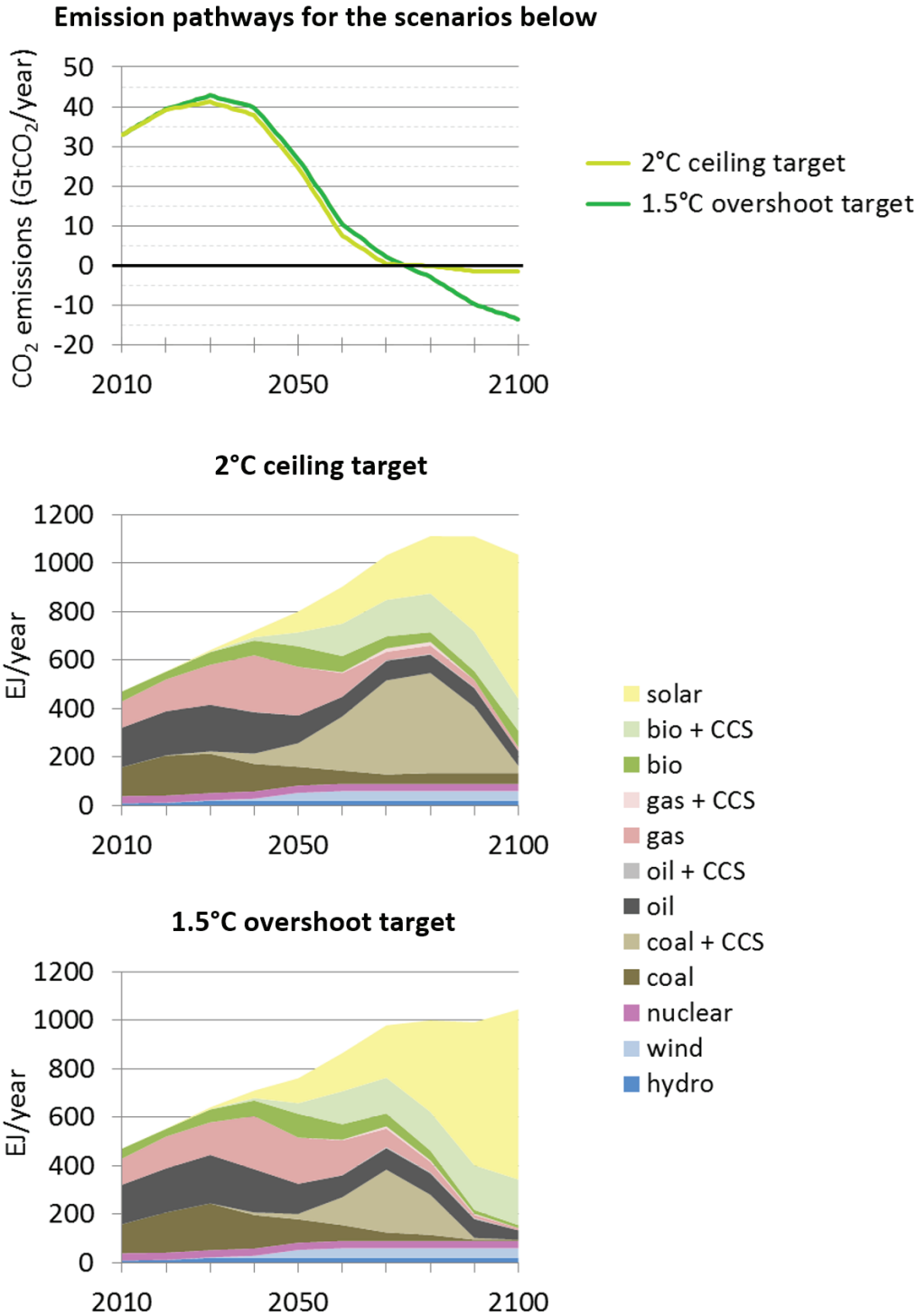

Figure 5-4. **CO_2 emission pathways and primary energy supply to 2100.** Emission pathways for the 2°C ceiling target with BECCS (light green) and the 1.5°C overshoot target with BECCS (dark green). Below, primary energy supply for the 2°C ceiling target with BECCS (middle) and the 1.5°C overshoot target with BECCS (bottom). Primary energy supply that has carbon capture applied is shown in lighter color shades.

Finally, we note that BECCS enables temperature levels to be reached that are otherwise infeasible. Global warming can be reversed using NETs, but not quickly enough to serve as an "emergency brake" when climate damages already are upon us. The maximum rate of post-2100 temperature decline that is observed with our model framework is about 1°C/century including abatement of non-CO_2 greenhouse gases, or about 0.6°C/century when isolating the contribution of BECCS.

5.5 Discussion

BECCS is only one of several potentially important NETs. Other options include afforestation and reforestation (to increase carbon stored in trees and their soil), direct air capture (chemical capture of CO_2 from ambient air) with carbon storage, soil carbon sequestration (changed agricultural practices that improve uptake and retention of carbon in soil), biochar (pyrolysis of biomass to charcoal for use as soil improvement), ocean fertilization (enhancing biological ocean carbon uptake by fertilizing nutrient-limited areas) and enhanced weathering (engineering minerals to enhance natural weathering, i.e. chemical uptake of CO_2 from the air).

Any of these NETs could substitute for BECCS in our study. However, BECCS is the only NET with major impact on the energy system. Other NETs have more limited energy system effects. For example, direct air capture increases electricity demand and biochar requires large-scale pyrolysis capacity and produces gaseous biproducts that could be used in the energy sector.

The NETs have a wide range of different properties, restrictions and side-effects (Fuss et al., 2018). For example, unlike BECCS, afforestation and increased soil carbon are associated with a saturation of CO_2 removal over time. Also, sequestration in these terrestrial carbon stocks is reversible and may be inherently vulnerable (Fuss et al., 2014). An example could be risk of sudden carbon release in large-scale wildfires (Lomax et al., 2015).

Perhaps the most limiting physical constraint on BECCS is the global sustainable biomass resource, especially in relation to other needs for land and biomass, notably food security and biodiversity (e.g. Fuss et al. 2014). Estimates of global sustainable biomass resource in 2050 to 2100 range from 30 EJ/year to over 600 EJ/year depending on assumed trends in diet, crop yields, land use and population (Lomax et al. 2015). In paper 3 we test a range of 100 EJ/year to 300 EJ/year, based on the IPCC Special Report on Renewables (Chum et al. 2011). Anderson & Peters (2016) also highlight the logistics problem of "collating and transporting vast quantities of bioenergy—equivalent to up to half of the total global primary energy consumption".

Estimated abatement costs and sequestering potentials of NETs in 2050 based on Minx et al. (2018) is shown in figure 5-5. Note that this represents a relatively short-term view compared to the time horizon used in our study, and the original figure in Minx et al. makes clear that the annual carbon removal potential of BECCS and direct air capture is expected in increase after 2050. Nevertheless, the availability of other low-cost NET options calls into question an exclusive focus on BECCS. Minx et al. emphasize this explicitly: "any single NET is unlikely to sustainably achieve the large NETs deployment observed in many 1.5°C and 2°C mitigation scenarios. Yet, portfolios of multiple NETs, each deployed at modest scales, could be invaluable for reaching the climate goals."

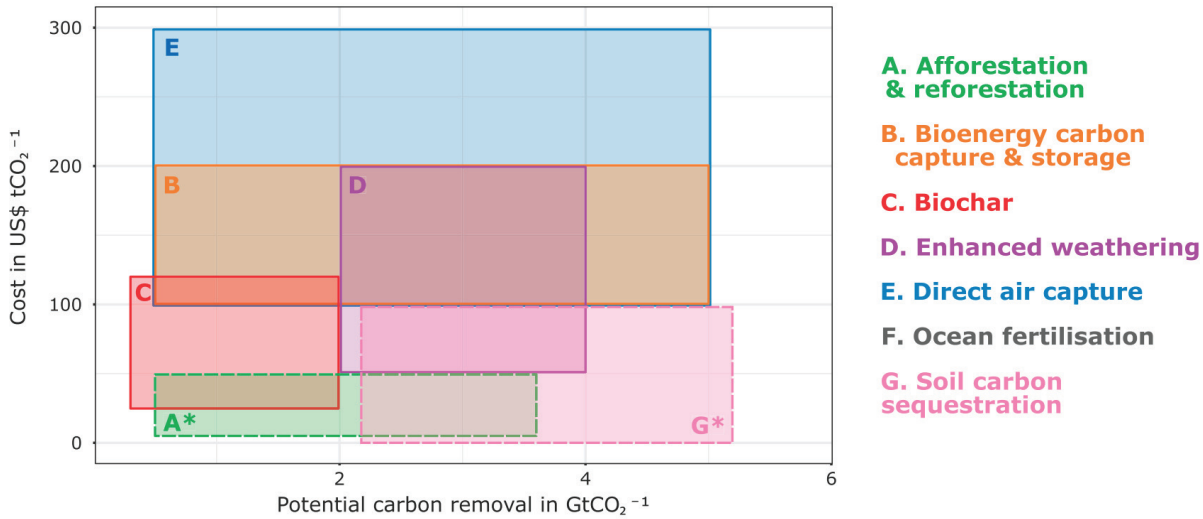

Figure 5-5. Estimated costs and annual potential carbon removal of negative emission technologies in 2050, adapted from Minx et al. (2018) and Fuss et al. (2018). (No box is shown for ocean fertilization.)

The cost of some of the NET options may appear to be somewhat high compared to more established mitigation options. However, Fuss et al. (2014) argues that mitigation pathways excluding NETs tend to be substantially more expensive than pathways including NETs. This can be explained by the second mechanism as noted above and in paper 3; postponing emission reductions has economic benefit when future costs are discounted.

Studies using integrated assessment models show that meeting a 1.5°C target increasingly requires large-scale deployment of NETs (Anderson & Peters 2016, Minx 2018). Many studies of the 2°C target also use NETs, but the target is still feasible without NETs (Minx 2018). However, there is a striking gap between implied up-

scaling in model pathways and real world progress in deployment and policy support of CCS and NETs (Minx 2018). Lomax et al. (2015) suggest that this may be partially due to uncertainty of future technology development of BECCS and other NETs, but cautions that uncertainties should not be used to justify inaction in the near term, but rather to start learning-by-doing to enable future scale-up.

Some authors (undersigned included) view development of BECCS and NETs as an insurance policy that may increase flexibility in reaching a wider range of climate targets in the future, and therefore require deployment and policies in the present. Others warn that they might become "a dangerous distraction" (Fuss 2014) or "an unjust and high-stakes gamble" (Anderson & Peters 2016). The latter also argue that mitigation should proceed on the premise that NETs will not work at scale. I concede that point if NET-skeptics concede the point on developing the technology.

Brief notes on the method

In this study we chose to hard-link an energy model with a climate model. We briefly considered a soft-linking approach, in which the two models were iterated until they converged to a common solution with agreement on chosen interface variables (in this case probably energy-related CO_2 emissions and CO_2 prices). When soft-linking works and the iteration converges, it is like finding a feasible internally consistent solution to the combined problem. But convergence is not guaranteed; infinite oscillations may occur. Even when a feasible solution is found, there is no guarantee of it being a least-cost solution to the linked problem. We soon decided to proceed with hard-linking, because find optimal solutions was important for drawing conclusions on the cost implications of BECCS.

A trickier question is: did we really need the energy model at all? Much modeling effort was expended to integrate the two separate models. But in the end, nearly the entire paper was about emission pathways and climate dynamics with almost no discussion about energy system developments. We could probably have written the same paper using just the climate model, making reasonable assumptions about the use of BECCS in the energy system.

As the saying goes: "if all you have is a hammer, everything looks like a nail". As an energy system modeler, I may have been a bit too enthusiastic about hammering away without considering the options.

6 Modeling variable renewables with resource-based slicing (paper 4)

6.1 Background

The share of solar- and wind power in the electricity supply sector is expected to increase significantly as we begin transitioning towards a carbon-free society. Many researchers are now studying 100% renewable energy scenarios (e.g. Jacobson et al., 2017), in which integration of variable renewables becomes a major challenge. Some of the most important options for integrating large amounts of solar and wind electricity include increasing flexible dispatchable generation capacity, electricity storage at intraday, interday and perhaps seasonal timescales, and interregional power trade.

Long-term energy transitions have historically been studied using bottom-up energy system models like MARKAL, MESSAGE or TIMES. These models are quite large, with dozens to hundreds of technology options in multiple energy supply and end use sectors, multiple regions and time horizons of 50 to 100 years. Because their sheer size compels some sacrifices, these models often use a simplified representation of a year using time slices. This involves dividing a year into a small number of segments, typically three seasons (winter, summer, intermediate) and two daily periods (day, night). Sometimes a few extra time periods are used for weekends or demand peaks. Supply technologies are parameterized using an average capacity factor for each time slice.

This setup is perfectly acceptable for traditional energy systems dominated by thermal supply technologies. The time slice division results in a good approximation of the load duration curve of (primarily electricity) demand. When all regions have the same time divisions it can capture electricity trade, which involves energy transfer from a time slice in a region to the same time slice of another region. Intraday

electricity storage can be modeled by allowing transfer between day and night periods of the same season, and seasonal storage by allowing transfer between arbitrary slices.

However, the scheme is inadequate for studying supply systems with high penetration of intermittent renewables, especially for wind power which lacks seasonal and daily regularity. Representing electricity supply using an average capacity factor in each time slice means that all variability is lost, and all slices will have similar output. Without explicitly representing variability, the model remains ignorant of sunny and windy periods that may require curtailment, as well as potential electricity shortages during dark and calm periods.

A way of sidestepping these problems altogether is to enforce a model constraint that limits the penetration of intermittent renewables to a level which can be easily integrated by regulating with dispatchable generation, often considered to be 20-30% of annual demand. We used an intermittency constraint like this in papers 1 and 2. This was actually a quite common method during the 1990s and early 2000s, when a 30% penetration level was thought to be many decades away. After the surprisingly rapid growth of solar PV and wind power during the past 20 years, many countries are approaching this level and some have already surpassed it.

6.2 Research questions

Instead of using conventional time slices based on season and time of day, would it be feasible to implement slicing based on solar and wind generation? If enough slices are used, this would by design capture solar and wind (co-)variability. This method can't easily be used for interregional electricity trade, since generation in a given hour might be allocated to different slices in different regions. However, there is an entire class of models with continent-sized regions that lack cross-border electricity trade, including global energy system models (e.g. MESSAGE, GET) and integrated assessment models.

Another difficulty would be how to treat short-term electricity storage. The reason is similar to the trade caveat above, namely that generation in consecutive hours may be allocated to different slices. Using time slices inherently means discarding chronological information, which is required for the correct management of short-term storage. Long-term storage such as power-to-gas or hydro reservoirs is still possible to implement in slicing models, as long as time-dependent losses can be assumed to be zero.

Would this type of resource-based slicing allow us to eliminate artificial upper bounds on variable generation? How can it be implemented in a global multisector

energy system model? And can we find a way of handling short-term storage despite the intrinsic difficulties?

6.3 Method

We extended the code of the GET model (Lehtveer and Hedenus, 2015) to add resource-based slicing to the electricity supply sector by adding new variables for electricity generation that are indexed by slice as well as technology, time period, etc. For simplicity, we chose in this implementation not to add slicing to energy variables in other sectors.

GET is a multisector global energy system model with ten continent-sized regions (see figure B1 in the appendix of paper 4). Electricity trade is not allowed between regions.

Solar and wind data were produced based on ECMWF ERA-Interim reanalysis data using an early version of the GIS code that is the focus of paper 5. In short, the code takes reanalysis and other public datasets as input along with user-defined parameter assumptions on land use, turbine density, maximum population density and many others. Its output consists of potentials for installed capacity and time series of capacity factors for solar PV and wind power, partitioned by resource class (i.e. quality) and model region. The most important differences between this early GIS analysis and the updated version in paper 5 are the lower spatial and temporal resolution of the ERA-Interim dataset (80 km and 3 hours compared to 31 km and 1 hour in paper 5) and the lower working resolution of the auxiliary spatial datasets (9 km compared to 1 km). We postpone further discussion of the GIS approach to the next chapter.

Two methods of calculating resource slices from 3-hour capacity factors were tested. In the first method that we call manual slicing, we classified each slice according to its level of solar and wind output. Slices were labeled “low solar – high wind” (for a windy night) or “high solar – mid wind” (clear skies with average wind). The number of levels used for each technology was varied in the paper, but here we assume three levels are used for both (high/mid/low for both solar and wind), which results in a total of nine slices.

Solar and wind output were then mapped to slices as follows. First we condensed the per-pixel time series given by the reanalysis data to a single “representative time series” of solar PV and wind power for each model region, by taking the geographical mean of 3-hour capacity factors in all grid cells with an average or better resource class. This is equivalent to assuming that PV panels and wind turbines are distributed uniformly over all good solar and wind sites of each region. Then we allocated each 3-hour time step to a slice based on the two-dimensional distribution

of solar and wind output in that time step. Finally, using the original per-pixel time series, we calculated average capacity factors for each technology, resource class, region and slice.

The other slicing method used k-means clustering to automatically classify the combined solar and wind outputs into slices. The slices produced by this method are not necessarily quantifiable by regular ranges of individual solar and wind output as in the manual slicing example. See figure A3 in the appendix of paper 4 for an example with 16 clusters.

To get a coarse representation of a load duration curve for electricity demand, we also assume that daytime demand (i.e. slices with high and mid solar output) is 15% higher than nighttime demand (slices with low solar).

Flexibility constraints were introduced for all thermal technologies and hydropower. The purpose was to prohibit ramping up and down from zero to full capacity between slices, which may represent time periods three hours apart.

Finally, we define a "slice transfer matrix" to roughly quantify short-term storage. Suppose we have a 12-hour storage technology and want to estimate limits of stored energy transfer from slice X to all other slices. We use the time series of allocated slices to determine the frequency of slices that occur within 12 hours after all time periods allocated to slice X. If say 20% of these potential destination slices are slice Y, then we assume a maximum of 20% of stored energy can be transferred from slice X to Y.

6.4 Results

Figures 6-1 to 6-3 show results from running a 450 ppm stabilization scenario using the GET model with 9-16 resource-based slices. The development of the aggregate global electricity production mix during 2010-2100 (figure 6-1) looks "reasonable" with its balanced mix of wind, solar, nuclear, hydro and fossil CCS. Variable electricity generation from wind and solar PV grows significantly and reaches a combined market share of 47% of annual global electricity in 2060, but the share then declines slowly to 42% by 2100. This is due to the decreasing marginal value of new wind and solar generation, as the best resource classes are exhausted and as implicit electricity prices (shadow prices) approach zero in slices with high variable generation. Note that this saturation takes place without the use of an intermittency constraint, thus validating our slicing method.

The regional electricity mixes[11] in 2100 (figure 6-2) are quite diverse, which reflects regional differences in resource quality of solar and wind generated by our GIS package. Regions with less attractive renewable options tend to use nuclear power, probably because of the limited carbon budget imposed by the concentration target (fossil CCS has some residual CO_2 emissions in GET).

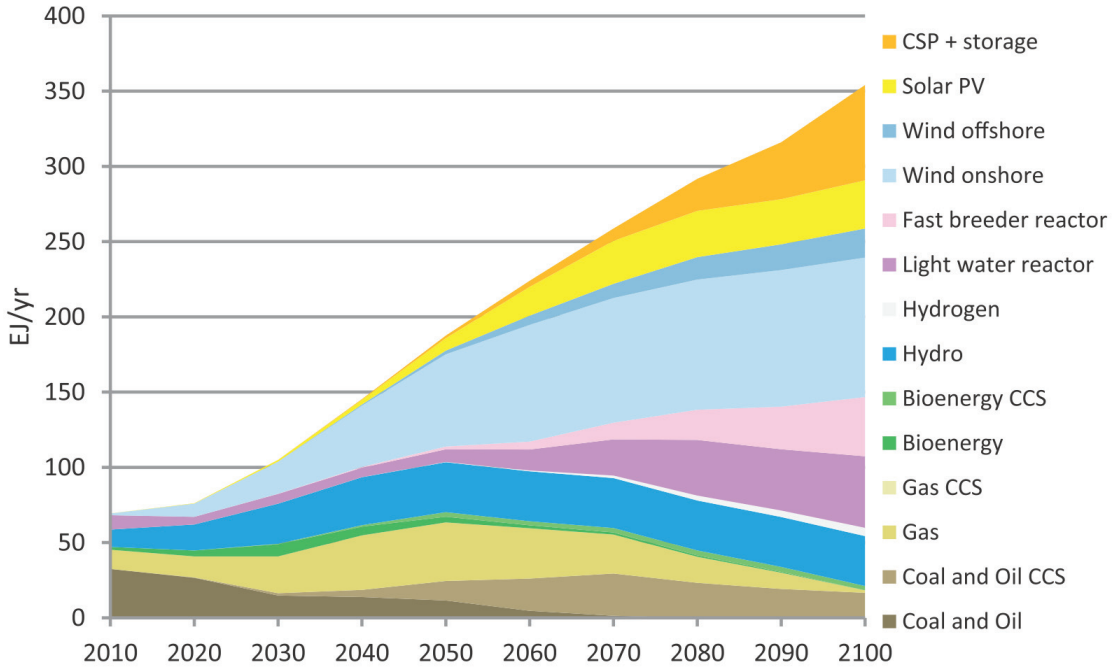

Figure 6-1. Global electricity production mix with the 450 ppm CO_2 scenario and clustering with 16 slices.

[11] Note that due to a graphical error, solar PV and CSP are shown in very similar shades of yellow.

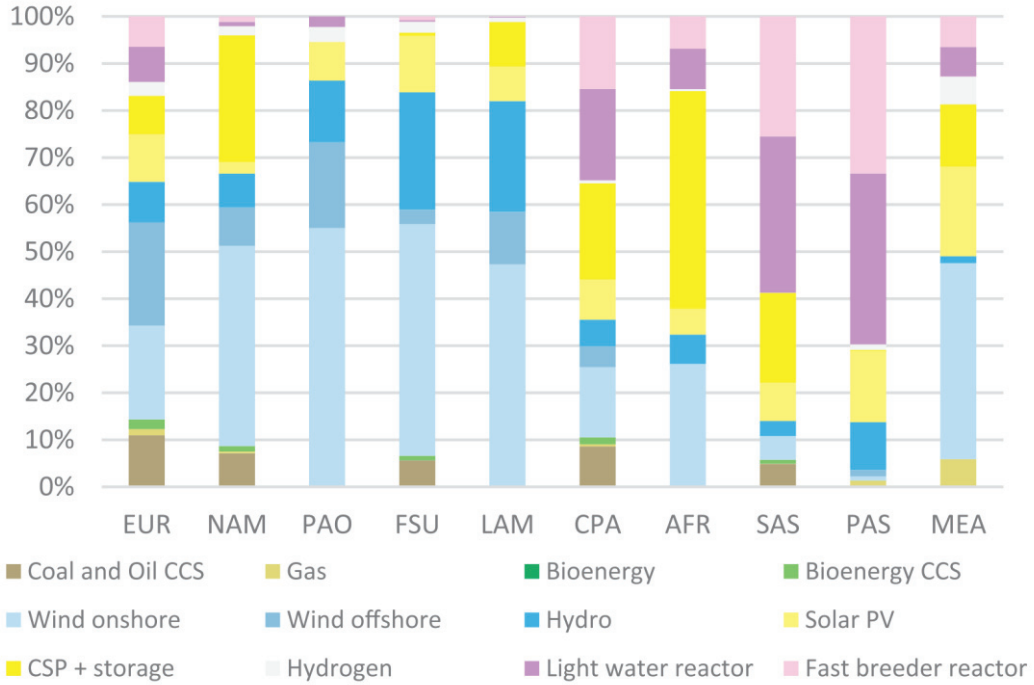

Figure 6-2. Regional electricity production mix in year 2100 with the 450 ppm CO_2 scenario and 16 clusters.

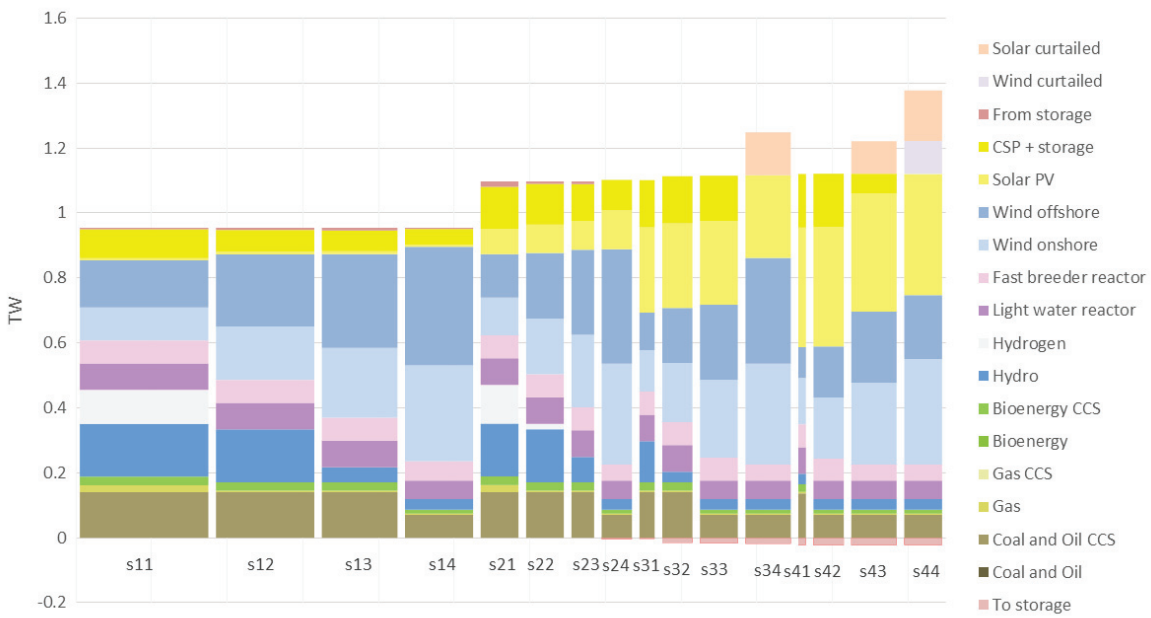

Figure 6-3. Electricity production mix in Europe year 2100 in the 450 ppm stabilization scenario, using 4x4 manual slicing. The width of each slice represents the share of hours that fall into that category.

Figure 6-3 illustrates the slicing dynamics of our model in the 4x4 manual slicing case. In this region (Europe), coal power with CCS and nuclear is used as a roughly constant base load, while natural gas with CCS, hydropower and CSP with thermal storage act as dispatchable intermediate generation, filling most of the net load gap left by solar PV and wind power. Note the use of hydrogen from power-to-gas and small amounts of short-term storage in figure 6-3[12]. There is also some curtailment in slices with high variable generation.

We also performed a series of model runs of the same scenario while varying the number and type of slices, see figure 6-4 (global) and figure 5 of paper 4 (Europe). We note that to a large extent, the runs have converged to the 64-slice solution already at 9 or 16 slices using both manual slicing and k-means clustering. However, a small exception to this is the apparent trade-off between solar PV and CSP generation, which continues to shift subtly even beyond 16 slices.

Overall we conclude that our conceptually simple resource-slicing method captures many properties of energy model dynamics with large shares of intermittent generation, but the drawbacks with respect to interregional electricity trade and short-term storage limit its suitability to global energy system models with continent-sized regions and integrated assessment models.

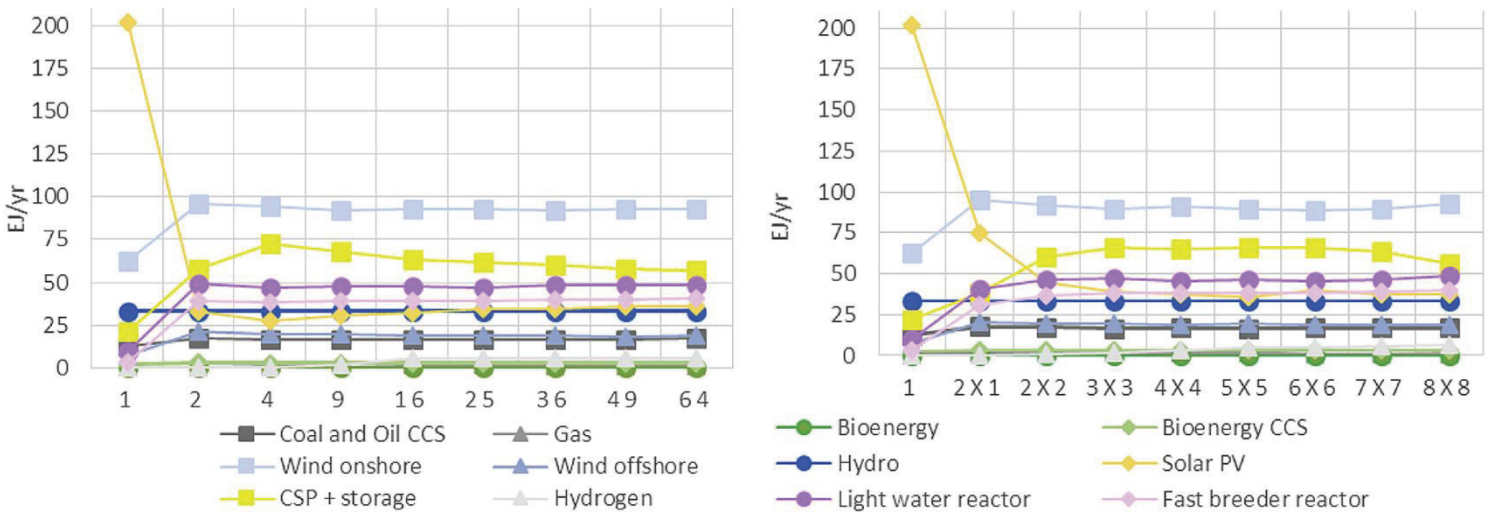

Figure 6-4. Global electricity mix at year 2100 for different number of slices with clustering (left) and manual slicing (right).

[12] I include this figure despite its similarity with figure 3 of paper 4, because the figure in the paper inexplicably does not show the (small) contribution from short-term storage.

6.5 Discussion

Method critique

In retrospect, I have some critique of the approach we used in paper 4. Our choice of only implement slicing for electricity supply and not for other sectors is somewhat strange, and could potentially cause complex interactions when electricity generation occurs outside the supply sector. Examples include the heating sector, which potentially interacts with power generation by combined heat and power (CHP) plants, heat pumps, and thermal storage (which can help integration of variable renewables), and the transport sector which interacts both by electricity use in trains and electric vehicles (EV) but also potentially by storing electricity in EV batteries. This choice was made partly for performance reasons and partly as a first development step, with the intention of expanding the slicing implementation later – though this has not yet happened.

It should also be emphasized that the use of the "slice transfer matrix" is something of a hack. It does not remotely provide the flexibility of properly implemented short-term storage in an hourly model. Nevertheless, we do believe it somewhat mitigates the loss of chronological time periods.

Perhaps the greatest weakness of paper 4 is that we were not able to compare our resource-based slicing approach directly with results from a more detailed model with hourly time resolution. This could have provided a baseline "correct" result to evaluate our slicing approximation. We simply did not have an hourly model available when paper 4 was written. But using the new GlobalEnergyGIS package described in the next chapter, it would be interesting to revisit and re-evaluate paper 4. The GIS package can easily generate hourly input data for a global electricity model with the same ten regions as in the GET model. Then two possible comparisons come to mind. First, we can take installed capacities for some year from the GET model, plug them into the hourly model presented in paper 5 and compare the resulting hourly electricity dispatch with the dispatch in the GET slices. Alternatively, we can extract the power supply sector with resource slicing from GET as a separate (much smaller) model, and compare investment pathways with a dynamic perfect-foresight version of the hourly capacity expansion model in paper 5.

In any case, performing model experiments in the relatively large global multisector GET model was probably a mistake, and likely caused weeks or months of unnecessary work. Small tailor-made models with fast run times and more easily digested results are almost certainly a better fit for model experiments. Once the new

method has been developed, tested and fully understood, it can be scaled up and implemented in larger models.

An earlier study

Our slicing methodology is essentially identical in all respects to the system states approach described by Wogrin (2014), including the use of a transition matrix to represent short-term storage. We cited this earlier work in paper 4 in the context of the transition matrix, but we did not realize at the time how similar the general approach was to ours. Other authors call this method the integral approach (Reichenberg et al., 2018) or the enhanced integral approach (Poncelet, 2018). Both Wogrin and Reichenberg use relatively small experimental models (as we propose above) and are able to test the approach in comparison with chronological 3-hour time steps. They conclude that the approach provides similar solutions to the hourly model while solving significantly faster, but note the downsides with respect to electricity trade and storage.

Representative days

Browsing the recent modeling literature gives the impression that the modeling community may be converging on the use of representative days as an acceptable method for reducing time resolution in energy models, while retaining the ability to analyze systems with high penetration of variable renewables (e.g. Ludig et al., 2011; Nahmmacher et al., 2016; Poncelet et al., 2017). This method involves selecting a small number of days with "representative" solar and wind output, often with a variant of a clustering algorithm, and using them as a proxy for an entire year of data.

When reducing time resolution in models, some potential problem areas are electricity trade, which requires simultaneous time periods in multiple (possibly distant) regions, and electricity storage at various timescales from hours to days to seasons (Reichenberg 2018).

Since representative days retain time period chronology within the hours (or sometimes 3-hour periods) of each day, they can correctly model intraday storage, including e.g. time-shifting solar energy from day to night using pumped hydro storage, batteries or CSP thermal storage. However, interday storage is not possible since chronology between days is lost.

Since interday variability is an important characteristic of solar and wind power, some authors use representative groups of days or even weeks to preserve interday chronology (Nagl et al., 2013; Schaber et al., 2012). However, this can significantly increase the number of time steps required to capture a sufficient amount of total variability. Also, since regional weather patterns are enduring and wind fluctuations

can last several weeks, even a representative week or two is not sufficient to capture the chronology of an entire wind "cycle".

On longer timescales other storage options like hydro reservoirs or power-to-gas may be used. These can be modeled using round trip losses and can be implemented in models using representative days or slices. However, self-discharge losses require chronology of time periods and therefore cannot be accurately modeled this way.

When representative days are used in models with interregional electricity trade, days must be selected based on aggregate solar and wind generation over all regions, and not days which may be more representative in individual regions. This is because trade is only possible if the same hours are represented in all regions. This constraint may limit the usefulness of the approach, since it may be difficult to find representative days on a continental scale.

A promising new method was proposed by Pineda (2018) that may outperform both resource-based slicing (a.k.a. the system states approach a.k.a. the integral method) as well as representative days. It involves using a clustering algorithm that merges consecutive time periods and therefore significantly reduces the number of time periods while retaining their chronology. This method was brought to my attention too late to evaluate it for this thesis (mid-December 2019), but I very much look forward to testing it soon after January 17.

7 GIS-based generation of renewable input data for energy models (paper 5)

7.1 Background

When developing a new energy model, a significant part of the work involved – perhaps even the lion's share – is building the input database for the region under study. Technological parameters like costs, efficiencies and lifetimes can usually be borrowed from other models since the energy technology market tends to be global in scope, but other parameters like fuel costs, energy demand profiles, renewable output and future capacity potential are strongly dependent on local conditions and must be adapted to each new model region.

Sometimes modelers estimate hourly renewable output profiles using regional generation statistics from the local electricity market, a method that implicitly assumes that the geographical distribution of installed capacity will not change over time. This is not a safe assumption. For example, if the market is efficient, new wind farms will generally be introduced at windier, more profitable sites before less profitable ones. Alternatively, wind generation may be expected to increasingly move offshore over time to avoid the NIMBY effect. Both cases would significantly alter locations where new wind capacity is installed.

In recent years, the emergence of meteorological reanalysis data with high spatial and temporal resolution has enabled a new method for estimating wind or solar renewable generation at a given site. A reanalysis can be simply viewed as a retroactive weather forecast. It describes the global state of the atmosphere at a given time in the past using advanced meteorological models. It is more reliable than ordinary forecasts because it is updated with observations made after the fact. The ERA5 reanalysis (Copernicus 2017) that we use in paper 5 is produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) and provides data for

temperature, wind speed, humidity, solar insolation and many other variables. Each ERA5 variable is available hourly on a global grid with a resolution of 31 km, as well as for different pressure levels (i.e. altitude).

Reanalysis data have generally been extensively ground-validated for use in energy system analyses (e.g. Huber et al., 2014; Pfenninger and Staffell, 2016). However, the ERA5 reanalysis is a relatively new product and validation studies have only recently begun to appear in the literature (Olauson, 2018; Urraca et al., 2018). ERA5 tends to underestimate real wind speeds because the 31 km resolution is not sufficient to capture wind interactions with local topography (e.g. funneling effects in mountains) (Olsen et al., 2019). In paper 5 we attempt to compensate for this bias by calibrating ERA5 data with the Global Wind Atlas (DTU, 2019), a dataset with 1 km resolution.

7.2 Research objective

The ultimate goal of this project was to build a framework to support bottom-up modeling of electricity supply in any region of the world, with a focus on managing variability of renewables at high penetration levels. This required developing a GIS-based software package that could use global reanalysis and other datasets to estimate renewable input data for a bottom-up model with sufficient local accuracy. More specifically, we needed to estimate hourly output from solar PV, CSP, and onshore and offshore wind power as well as their potential installed capacity at any location.

Since a package like that could be of interest to the entire energy modeling community, we also wanted to release it with an open source license, in the hope of eventually attracting users who could provide quality control and perhaps even developers who might add features to the package. Releasing it as open source would also facilitate transparency and reproducibility of model applications.

The central principle of the resulting GIS package is that renewable input data can be generated by combining global datasets with global parameter assumptions, without relying on studies of renewable costs and potentials in individual countries. In other words, we use top-down assumptions to create bottom-up data. The main advantages of this approach are:

- Data can be generated automatically.
- Data can be generated for arbitrary regions of the world.
- The generated data is inherently self-consistent.

The main downside is that the analysis must be based on global datasets, which sometimes means not taking advantage of good data sources. For example, we do

not currently use maps of the existing transmission network in Europe. The global grid proxy that we use is based on gridded GDP and is considerably more uncertain.

7.3 Method

The following is an overview of the method used to generate renewable potentials and hourly capacity factors. For a more detailed description, see paper 5 and its supplementary material.

To generate input data for solar PV, CSP, and onshore and offshore wind power, we download relevant variables for direct and diffuse solar insolation and wind speeds from the ECMWF ERA5 reanalysis data repository for a given year. We also download other public datasets on administrative borders, gridded population and GDP in SSP scenarios, land cover, topography and protected areas.

A high-resolution global raster (1 km pixels by default) of model regions is constructed based on region definitions given by the user and datasets for administrative borders. Each pixel is assigned a resource class for solar and wind based on average annual capacity factors in the ERA5 reanalysis (for solar) or average annual wind speeds in the Global Wind Atlas (for wind). Other user-defined global parameter assumptions are used with auxiliary datasets to remove pixels which cannot be used for wind- and solar parks, e.g. due to being in a protected area or having too high population density. Renewable potentials for each region and resource class are calculated by assuming that a certain fraction of the area of each remaining pixel (another parameter) is available for solar- and wind farms. Finally, hourly capacity factors are obtained for solar by averaging hourly capacity factors from ERA5 data for each region and resource class. This implicitly assumes that solar PV is installed uniformly in each model region. Hourly capacity factors for wind are calculated similarly, but first hourly ERA5 wind speeds are scaled to match annual average wind speeds in the Global Wind Atlas in each pixel. This extra step is done to capture geographical variations in wind power output caused by local differences in topography and land cover at a spatial resolution of 1 km that are otherwise smoothed at the 31 km resolution of ERA5. An assumed wind turbine model is used to convert wind speeds to capacity factors.

To calculate existing capacity and future potential for hydropower, we combine public databases on currently existing plants and dams (Lehner et al., 2011; World Resources Institute, 2018) with future potentials, costs, reservoir size and monthly inflow from Gernaat et al. (2017).

Estimates of HVDC transmission costs and losses are calculated based on distances between population-weighted regional centers, and whether the connection is entirely on land or partially marine.

A machine learning approach is used to generate synthetic hourly electricity demand series that describe current demand in any country or region in the world, which we extend to future years using regional SSP scenarios. We fit a gradient boosting regression model to time series of electricity demand for 44 countries based on a small number of independent variables, including GDP, hourly and monthly temperatures and calendar indicators such as hour of the day and weekday or weekend. Only variables that could be easily parameterized using public statistics were selected. Predictions in some countries could in principle be improved using data on e.g. current industrial structure or installed capacity of electrical heating and cooling (Toktarova et al., 2019), but we deliberately excluded variables that were either not globally available or could not be reliably extrapolated into the distant future.

Finally, we link the resulting GIS-generated input data to a new capacity expansion model of a generic electricity supply system in arbitrary world regions. The model optimizes capacity investment and dispatch for the electricity sector during one year with hourly time resolution using a greenfield approach (i.e. all technologies must be built up "from scratch" except hydropower, which inherits its current existing capacity).

7.4 Results and conclusions

Aggregate continuous cost-supply curves for wind power and solar PV in Europe and China were constructed using the GIS package by configuring it with several hundred resource classes (instead of five classes when generating input data for the energy model), see figure 7-1. They demonstrate the differences in resource endowment between Europe and China. China has virtually unlimited access to low cost solar electricity (particularly in the sparsely populated western regions), but wind resources are more limited and costs increase steadily as the best sites are taken into use. In Europe costs increase in a similar way for solar electricity as installations must occur in cloudier more northern sites, while the middle region of the curve is relatively flat for wind, reflecting a general availability of decent wind resources.

In both regions, solar electricity is available at considerably lower levelized cost than wind power. Nevertheless, in the energy model runs using strict limits on CO_2 emissions, the optimal share of wind power is roughly twice as high as that of solar in both regions. This reflects the declining value of solar electricity as daytime generation becomes more saturated.

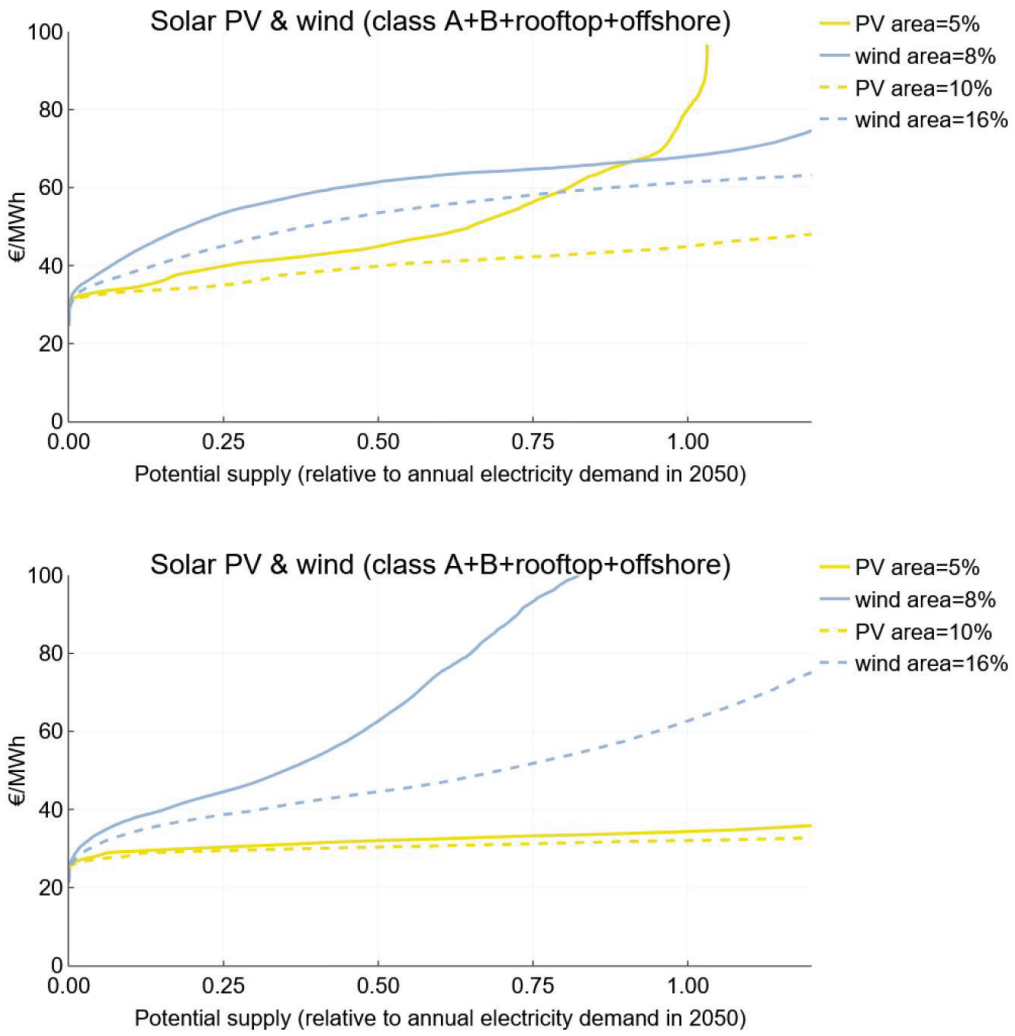

Figure 7-1. Cost-supply curves for all solar PV and wind classes in Europe (top) and China (bottom), with default (solid lines) and high assumptions (dashed lines) for land availability. The figure labels show the land area assumptions used for classes A1-A5 (i.e. pixels with electricity access). Land availability in classes B1-B5 (remote areas requiring additional grid investments) is assumed to twice as large.

Despite its simplicity, the energy model captures this effect as well as several other system effects typical of power systems approaching 100% share of renewables. Examples include the benefits of geographical smoothing, the importance of electricity storage and cross-border electricity trade to deal with solar and wind variability, and the strikingly large amounts of curtailment during daytime peaks.

Cross-validation testing of the synthetic demand module shows that demand predictions are (perhaps surprisingly) accurate over hourly, weekly and seasonal time scales for most countries, despite the generic approach and the small number of independent variables used in the regression. Some countries (roughly 10-15%) have significant prediction errors of daily demand variability, but this mostly happens

with non-OECD countries which are underrepresented in our database of real demand time series. More data from developing countries could likely improve the model in this respect.

More data may also be required to accurately portray a typical year of renewable generation. Both solar and wind generation are subject to considerable inter-annual variability, and it has been observed that models that only use a single year of renewable input data show a wide range of "optimal" installed capacities depending on which data year was selected (Pfenninger, 2017). The GlobalEnergyGIS package allows for download and preparation of arbitrary years of ERA5 input data.

Overall, our model runs of a future European electricity system with high share of renewables are roughly in line with results from more detailed models, despite our top-down approach using global datasets, synthetic demand and a simpler and more generic optimization model. This gives confidence that our modeling framework is sufficiently robust to be applicable to less studied regions of the world.

Indeed, in addition to the sample model application presented in paper 5, my colleagues have already used the GlobalEnergyGIS package as the basis for several other case studies, including deep decarbonization scenarios in a future Eurasian supergrid (Reichenberg et al., 2019), benefits of integrating electricity generation in the Middle East and North Africa (Ek-Fälth et al., 2019), and a study of nuclear power in the Nordic power system (Kan et al., 2019). Collectively these studies illustrate the flexibility and general applicability of our GIS package.

7.5 Future work

The GlobalEnergyGIS package was set up to partition renewable resource potentials into an arbitrary number of resource classes within each model region, thereby producing supply curves for each region. Other modeling groups choose not to use resource classes and instead opt for smaller region size, which has a similar effect on regionally aggregated results (e.g. the European power mix) at the cost of losing heterogeneity in individual regions. There is a trade-off between region size and number of resource classes which effects regional accuracy of results and computational work needed to solve the model. This is an interesting potential topic of future research.

I would also very much like to expand the GIS analysis made for paper 5. The uncertainty involving the "remaining land" parameter could perhaps be reduced or made endogenous to the model by estimating land costs and allowing a range of values for this parameter. I would also like to improve the analysis of hydropower

by using a hydrology model that covers locations above 60 degrees northern latitude, that expands the representation of water inflow from monthly averages to hourly inflow and that can (somehow) capture cascades of hydropower plants along the same river.

Further, the estimation of renewable supply potential could be expanded to include geothermal and bioenergy resources. The current use of a local GDP proxy to represent grid access could be replaced with an improved representation of existing and potential future transmission lines. Finally, location and infrastructure for fossil fuels and carbon storage potential could be added.

In other words: the GIS package as presented in paper 5 is very much a work in progress. In the long term my ambition is to have it automatically generate virtually all regionally specific input data for energy models.

7 GIS-BASED GENERATION OF RENEWABLE INPUT DATA FOR ENERGY MODELS (PAPER 5)

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