Internalizing technological development in energy systems models

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Contents

1. Introduction

Throughout the history of mankind, technological change in the energy sector has been a cornerstone of progress. Energy-related innovations such as the discovery of fire, the taming of animals for farm work, the development of metallurgy, the exploitation of flowing resources in windmills and water wheels, mechanization based on steam engines, the invention of internal combustion engines for transportation and the use of electricity for transmission and distribution of energy continue to have tremendous impact on all aspects of society.

However, energy use always affects the environment. Previously, negative environmental effects usually only had a local or regional extent, but now the widespread use of energy is beginning to have repercussions on a global scale. Global climate change caused by emissions of greenhouse gases, mainly carbon dioxide (CO_2) produced by combustion of fossil fuels, is currently a major environmental concern. The prospects of reversing trends of energy demand by for example accepting lower standards of living are probably very low. Quite the contrary: global demands of energy services are expected to increase substantially as developing regions of the world aspire to western standards.

Instead, it is hoped that technological development may solve the problem it has given rise to. Emerging high-efficiency energy technologies, especially based on renewable energy sources, may enable the transition to a sustainable CO_2-free energy system. The possibility, cost and time frame of such a transition is a focus for CO_2-mitigation studies by the Intergovernmental Panel on Climate Change (IPCC), which form a basis for international negotiations of emission reduction strategies by policy-makers. In such studies, energy systems models are important tools.

Energy systems models

An energy systems model can be characterized as a simplified, formalized representation of a real energy system. Often the system's components and dynamics are described using mathematical relations, which makes a computerized model implementation particularly appropriate. The scientific advantage of a formal model-based methodology is that it adds consistency, reproducibility and a common platform for communication to the analysis.

The ultimate purpose of energy systems models is to provide policy-makers with decision support in complex planning situations. Models are especially suited to answer "what-if" questions, thereby generating qualitative and sometimes quantitative insights into the system-in-focus. Typical applications include determining probable effects of new energy taxation, estimating costs of a nuclear phase-out and assessing environmental and economical benefits of international electricity trade.

There are two different methodological approaches to energy systems modelling, often labeled top-down and bottom-up. Top-down models are economy-oriented models with energy included as a subsector of the overall economy. Model dynamics are mainly induced by price changes, which influence the energy system indirectly through the economy. Top-down models are not given further consideration in this report.

Bottom-up or systems engineering models are technology-oriented optimization or simulation models of the technical energy system in relation to its environment. In these models, existing and potential energy flows are described in detail from resource extraction, via large-scale conversion, transmission, distribution, small-scale conversion to end use. Technological options are specified explicitly, using both technical and economical parameters.

In figure 1, the technical energy system is displayed in relation to four critical factors in the system environment (Wene and Rydén 1988). The factors are energy demand, energy sources, physical environment and technological development. Most bottom-up

models treat all four factors exogenously; i.e. relevant parameters are supplied as external input to the model[1]. A proposed system is regarded as feasible from a modelling perspective when it satisfies both internal technical constraints as well as external constraints given by these four factors.

The usual objective in these models is to find the feasible system with the lowest cost; this solution is considered to be optimal. Cost minimization is not the only possible criterion, but since low costs are always desirable, it filters interesting alternatives out of a multitude of feasible solutions.
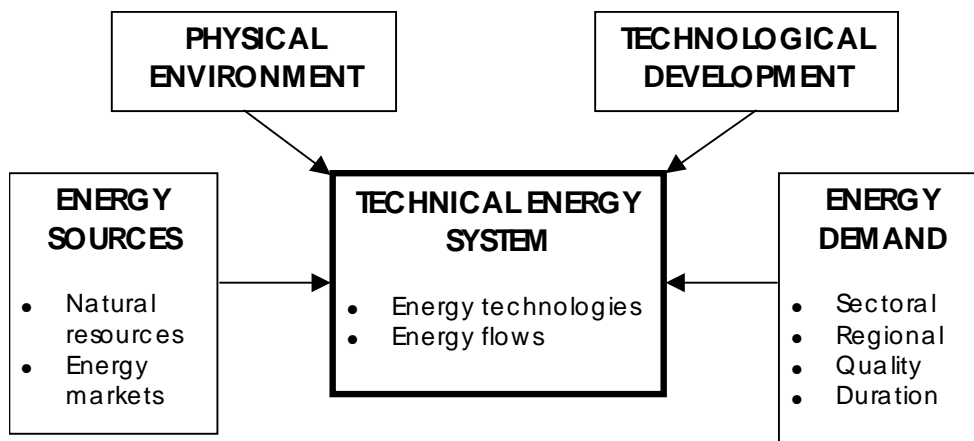

FIGURE 1   The technical energy system and four factors in the system environment.

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. However, most existing models are seriously limited in their treatment of technological development: improvements in individual technologies can only be considered by exogenous assumptions of future development paths. The models are therefore by design blind to possibilities of learning-by-doing, i.e. technological

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[1] Exceptions to this are e.g. the use of supply/cost curves to determine fuel prices internally (endogenous energy sources) and price-elastic demands (endogenous energy demand).

development induced by actual market implementation and experience. This deficiency can be very unfavorable to emerging technologies, which hinge critically on future development prospects.

An alternative method of treating technological development is by relating investment costs to accumulated experience of a technology using experience curves. These curves quantify learning-by-doing in a simple 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.

The research question is therefore threefold:

- Is internalization of experience curves in energy systems models feasible?

- How can this be implemented?

- What new insights can be provided with a model with internalized experience curves?

Chapter overview

The remainder of this report has the following structure:

Chapter 2 is a survey of the literature on technological development and experience curves. Relevant concepts and terminology are introduced here.

Chapter 3 is a description of the GENIE model, an energy systems engineering model with internalized technological development using experience curves.

Chapter 4 is a demonstration application of GENIE to the global electricity system. New modelling insights are presented, e.g. the risk of technology lock-in.

Chapter 5 summarizes conclusions and indicates directions of future work.

2. Technological development

In this chapter, several important concepts from the literature on technological development are introduced and discussed. Traditional methods of treating technological development in energy systems models are briefly reviewed, after which the use of experience curves is presented as a more refined alternative.

Dynamics of technical change

In 1980, a national referendum was held in Sweden to decide on the future of nuclear power. It was decided that nuclear power should be phased out as new, preferably renewable, alternatives become available, at a rate which does not jeopardize employment or welfare. In other words, await technology development. To support this development, energy research was given a large financial boost, but there were no significant commercialization or market support efforts.

Today, 17 years later, no nuclear reactor has yet been shut down. Two decades of low electricity prices have led to a lock-in of electricity-intensive applications such as extensive use of direct electric heating of residences. The low prices have removed commercial incentive to develop new technologies. The political discourse is largely unchanged: in the absence of viable alternatives, do research and await progress.

But, a similar system reformation was high on the political agenda in 1980: the ambition to reduce oil dependency. The Swedish district heating system was then completely dominated by oil combustion. A variety of market incentives including e.g. investment subsidies and fossil fuel taxes, aided by a high oil price in the early 80s, proved very effective, completely transforming the district heating system within a decade, see figure 2. The speed of this change is remarkable, considering the recognized inertia of large energy systems.
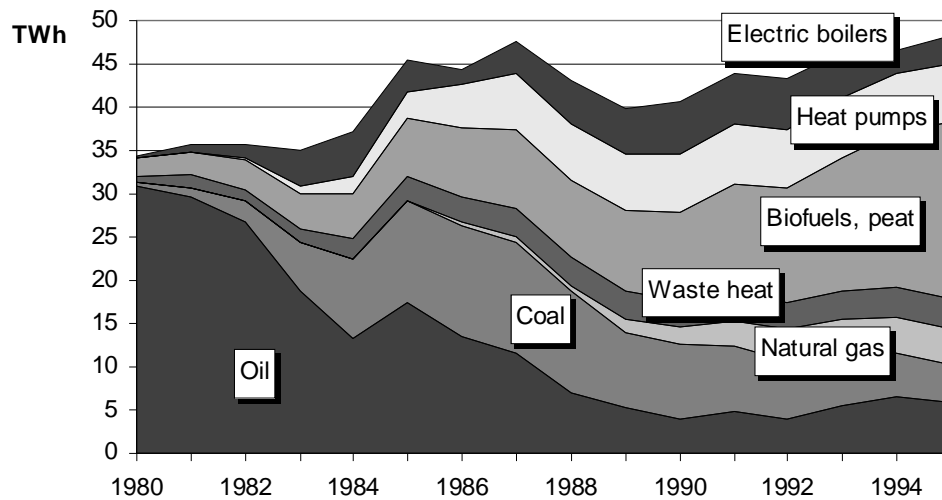
FIGURE 2 Supply of district heating in Sweden, 1980-1995.

Induced technological development

The two examples above illustrate the fundamental difference between *autonomous* and *induced* technical change. The Swedish nuclear policy appears to reflect a belief in spontaneous or autonomous technological development. In this view, sufficient R&D will bring a technology from infancy to potential large-scale deployment. Accumulation of technical knowledge proceeds regularly with ongoing R&D efforts, independent of market conditions. Actual implementation in excess of demonstration is not necessary to reach full technical potential.

In contrast, the technical change of the Swedish district heating system was not primarily a product of R&D; it was induced by market-related pressures enhanced by economic instruments placed on the system by the government. It is an example of induced technological development, a concept that has recently received considerable attention in the energy policy literature, see e.g. Grubb (1997) and Nakicenovic (1996). The basic idea is that systemic change is induced by need. Energy technologies and systems adapt over time to accommodate external pressures, such as price competition, meeting the will-to-pay of a new market niche or fulfilling performance and emission requirements.

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Both views of the dynamics of technology development are supported in the scientific literature. This is apparent in the literature on climate change mitigation, a field in which future technological development is one of the key uncertainties. For instance, Wigley et al. (1996) suggest that technical progress is a factor (among others) that may justify deferring CO_2 emissions abatement. I.e., if we postpone action until new low-carbon energy technologies become cheaper and more efficient (as a result of R&D), abatement costs can be significantly decreased. Wigley et al. thus appear to support an autonomous view of technical progress.

This paper sparked the so-called timing-debate among integrated assessment scientists. Both Grubb (1997) and Nakicenovic (1996) react, protesting that the postponement strategy is infeasible. Nakicenovic argues that the dynamics of technological change is a cumulative process of learning-by-doing, and concludes: "Unless there is dedicated, timely, and pronounced investment in these technologies, they are unlikely to be developed and thus become commercially viable and competitive in the market place." Grubb's view is similar: "It may be the act of abatement itself which starts to generate the possibility of long-term solutions to the energy/climate problem." A belief in induced technological development thus supports early action to mitigate climate change.

Technological push and market pull

Closely related to the issue of autonomous/induced technological development are the complementary forces technological push/market pull (or supply push/demand pull). Technology push can be regarded as government sponsored efforts to advance new technology, using publicly funded R&D. The development resulting from the space program is an extreme example. Market pull can be characterized as demand pressures placed on a commercial technology. Typical examples of market pull are listed as external pressures above. The market pull may or may not be driven by policy measures such as investment subsidies, procurement efforts, favorable taxation, etc.

Most authors agree that both technology push and market pull efforts are necessary for effective technological development, but the appropriate balance is naturally a topic for discussion. Generally, the nature of support efforts should depend on the development stage of the technology (Ayres and Martinàs 1992). An infant technology primarily needs product R&D, in childhood both product R&D and market establishment incentives are necessary, while adolescence marks a shift to process R&D and market support efforts. The recent emphasis on market pull in the literature could perhaps be regarded as a reaction to the nearly exclusive historical focus on technology push.

These issues are illustrated by contrasting Swedish and Danish wind power development efforts. Gipe (1995) writes:

"The Swedish wind program has emphasized R&D over deployment of the technology to an even greater degree than has the United States. And after nearly two decades of research, Sweden has less to show for its R&D expenditures than has any other country of the world. By 1994 Sweden has installed only 30 MW, nearly all outside the official Swedish wind program. Sweden's Scandinavian neighbor, Denmark, had installed 500 MW during the same period, spent only two-thirds as much on R&D, and created an industry exporting nearly $100 million in wind turbines per year."

Whereas the Swedish program focused on research and demonstration of extremely large wind turbines, the Danish program concentrated on establishing a market for small, relatively simple plants. The experience gained directed industrial efforts to develop progressively larger turbines, which have since become successfully commercialized. Gipe thus attributes the failure of the Swedish wind power program to an overemphasis on technology push, and the success of the Danish program to striking an adequate balance between technology push and market pull.

Learning-by-doing

The significance of market pull is that it enables learning-by-doing to take place. Learning-by-doing implies the qualitative assertion

that performance improves, and/or cost decreases, as experience of production increases. Its quantitative counterparts, learning curves and experience curves, are among the best empirically corroborated phenomena in industry (Messner 1997, Argote and Epple 1990, Ayres and Martinàs 1992). These curves are further discussed below. 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 the Nobel laureate Kenneth Arrow, who put forward the hypothesis that technical change in general can be ascribed to experience (Arrow 1962). Similarly, Nakicenovic (1996) regards learning-by-doing as a prerequisite for performance improvements, cost reductions and eventual diffusion.

The technology life cycle and niche markets

The performance improvements that take place during learning-by-doing may be manifested in successive design changes as the technology ages from infancy through its life cycle. During the childhood phase, diffusion is often relatively slow as a variety of designs compete for market shares. In this stage, the technology is critically dependent upon specialized niche markets, so-called nursing markets, which may help nurse the technology through its teething troubles to the point of commercial viability and self-sustained growth (Ehrnberg and Jacobsson 1997, Erickson and Maitland 1989). This marks the advent of the adolescent stage of the technology, featuring accelerated diffusion into a larger bridging market, bridging the gap between the nursing and mass markets. This phase is often characterized by the emergence of a dominant design, i.e. a certain design configuration that becomes adopted by crucial actors, with the previously mentioned R&D shift from product to process development taking place (Ehrnberg and Jacobsson 1997, Ayres and Martinàs 1992).

The progressive exploitation of niche markets is characteristic for the development of emerging technologies. Photovoltaic solar cells (PV) for instance, are currently regarded to be in the childhood stage. They appear in a variety of designs ranging from relatively expensive high-efficiency crystalline silicon wafers to relatively cheap low-efficiency thin films. The nursing markets upholding

the technology are mainly remote applications, where PV costs, high as they may be, are cheap compared with grid-line extension. The special benefits of the technology, being reliable, silent, fuel- and maintenance-free, also prove more favorable than alternative technologies in these applications. Still, these markets are relatively small. However, the U.S. Utility Photovoltaic Group has identified a huge potential bridging market, utilizing PV as transmission and distribution support of power lines using distributed generation. This market is estimated to be over 7000 MW (for the U.S. alone) at an installed system cost of 3 $/W (UPVG 1994). For comparison, current global annual sales are around 90 MW and system costs approximately 6 $/W. Still lower costs, less than 1 $/W, are probably necessary to reach the mass market of bulk power generation.

Inertia

However, new energy technologies face considerable inertia, even when they have major advantages. Historically, new supply technologies and fuels have required on the order of 50 years to diffuse significantly into the energy system. Some reasons for this delay are sunk costs of investment in long-lived equipment, e.g. power plants and infrastructure, social inertia, e.g. slow diffusion of information and resistance to accept new ideas, and general economic inertia to structural change, i.e. the difficulty of intersectoral transferal of capital and labor (Grubb et al. 1995).

Competing technologies and technological lock-in

Another related impediment to the adoption of new technologies is potential lock-in of more established technologies. When several technologies compete for a market of potential adopters, a technology that happens to get ahead gains advantages, which may tip the adoption market further in its favor, resulting in a lock-in situation (Arthur 1990). Arthur lists several of these advantages or sources of "increasing returns to adoption": learning-by-doing, scale economies in production, network externalities, informational increasing returns and technological interrelatedness. The first two require no further comment.

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Network externalities refer to advantages gained from belonging to a large network of users. For example, once the video system VHS obtained a significantly larger user network than the technically superior Betamax system, the VHS users benefited from larger availability of VHS-recorded products (Arthur 1990).

Informational increasing returns concerns advantages due to market familiarity: a more adopted technology has the advantage of being better known than its competitors, making it a more attractive option for risk-averse potential adopters.

Technological interrelatedness is synonymous with technological clustering. Technologies have often been observed to form symbiotic clusters of interrelated or interlocking systems (Grübler 1997). But whereas technological development within the cluster benefits from the symbiosis, technologies outside may be effectively locked-out (Grubb 1997). For example, it can be argued that electric vehicles are currently locked-out of a cluster consisting of gasoline-fueled automobiles and their associated infrastructure. An alternate technology such as ethanol-fueled automobiles, which shares internal combustion engines and fuel-pumping infrastructure with the existing cluster, will probably not be locked-out to the same degree.

Conventional modelling of technological development

Although technical change in general is an important driving force in macroeconomic top-down models, and the primary focus in technological bottom-up models, technological development is often treated somewhat summarily in both model types.

Top-down models

Technical change in top-down models of the energy system (and the economy) is usually accounted for by including a parameter called the Autonomous Energy Efficiency Improvement, or AEEI. The AEEI gives the rate at which structural change and penetration of new technologies may change the energy intensity of the economy at constant prices (Manne 1978, Manne and

Richels 1992, Nyström 1995). The parameter is specified exogenously, in the range of 0-1 %/year in most studies (Azar 1996). The definition of the AEEI, and indeed the name itself, suggests an autonomous view of technical change. Few top-down models have any features that correspond with a view of induced technological development. An exception is the TIME model (de Vries and Janssen 1996). Unfortunately, this paper could not be obtained in time for comment in this report.

Bottom-up models

Similarly, in bottom-up models, improvements in individual technologies are handled by making exogenous assumptions regarding the time development of technological investment costs. In such models, investments in developing technologies are often postponed until their costs become low. This strategy is infeasible since early investments are necessary to gain the technological experience that will realize the cost reduction.

A common way dealing with this problem is to limit growth rates over time, the idea being to force the model to invest during the expensive development phase. This method fails when the time horizon of the model is longer than the typical market penetration time (say 30 years), since the same postponement problem occurs. Therefore the method is of little use for CO_2-mitigation applications, which typically feature long time horizons. Indeed, most current model applications use time horizons of at least 30 years.

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. In other words, conventional bottom-up models also adhere to the concept of autonomous technological development. This is only acceptable for applications where most technological development occurs outside the system-in-focus. For example, in a national study of Sweden's energy system, an autonomous view of technological development is appropriate since most development occurs on the international arena.

Current energy system models are therefore incapable of studying induced technological development, learning-by-doing effects and technological lock-in, issues of fundamental importance in understanding the dynamics of technical change within the energy system. To rectify this situation, these phenomena must be given a quantitative formulation. The simplest conceivable quantification of induced technological development is the so-called experience curve.

Experience curves

An experience curve (sometimes called a learning curve[2]) 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 as more development efforts are committed to a technology, more opportunities for reducing costs and improving performance will be found. Conversely, the better the price/performance of a technology, the more investments it will attract.

Experience curves have been observed in a wide range of 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). Usually, to facilitate data acquisition, selling price is used as a proxy for costs, and cumulative installed capacity as a proxy for experience. Figures 3 and 4 show experience curves for integrated circuits and photovoltaic solar cells respectively. Notice the long-term stability of the cost reductions, even over several orders of magnitude of increasing experience. This regularity lends support to the notion of using experience curves to assess future technological development. A more general observation of trends in long-term

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[2] 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, increased capital intensity in manufacturing and economies of scale.

technical change is made by Ausubel (1995): "The essential fact is that technological trajectories exist. Technical progress in many fields is quantifiable. Moreover, rates of growth or change tend to be self-consistent over long periods of time. [...] Thus, we may be able to predict quite usefully certain technical features of the world of 2050 or 2070 or even 2100."
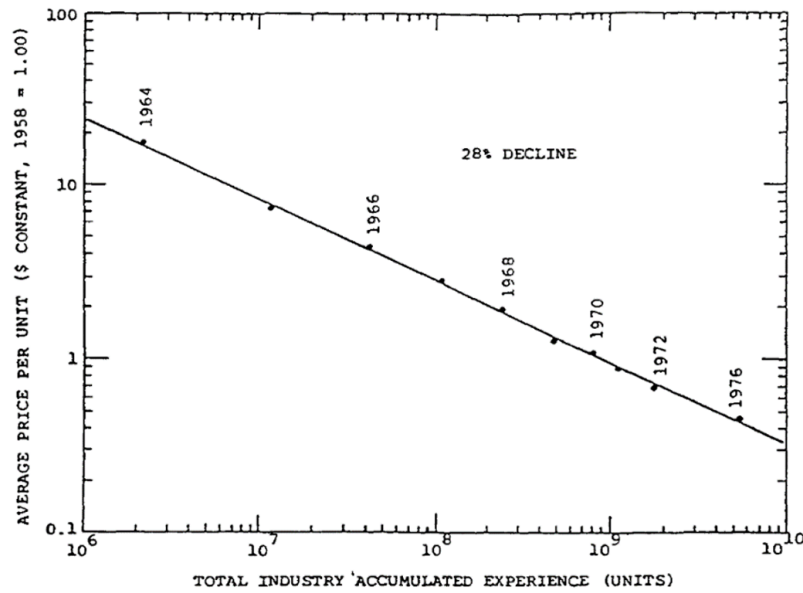

FIGURE 3   Experience curve for integrated circuits, 1964-1976 (Ayres and Martinàs 1992).
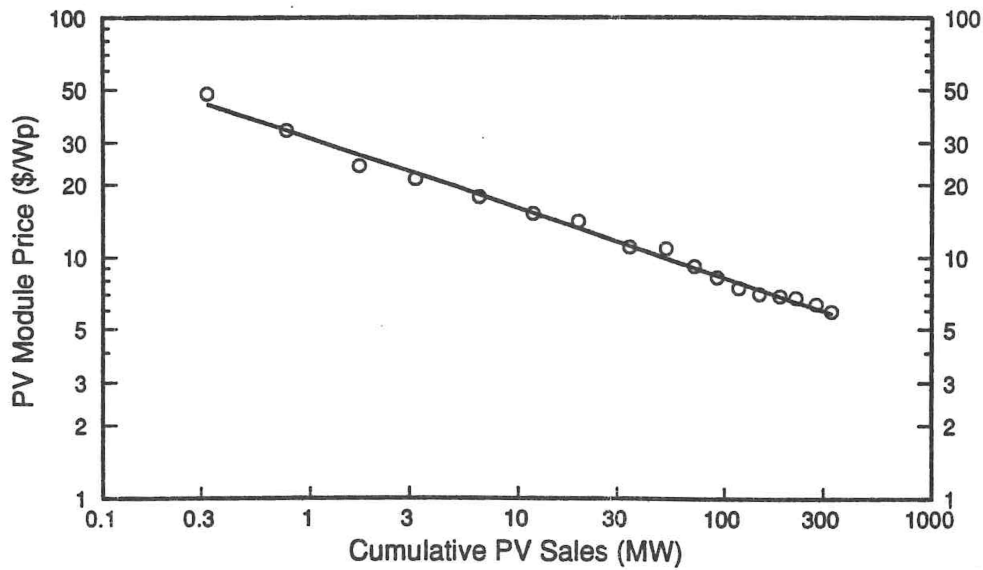

FIGURE 4   Experience curve for photovoltaic modules, 1976-1992 (Williams and Terzian 1993).

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The experience curve has a simple mathematical formulation:

$$C(E) = \frac{C_0}{\left(\dfrac{E}{E_0}\right)^\alpha} \qquad \text{with } \alpha \text{ given by} \quad PR = \frac{1}{2^\alpha}$$

Here $C(E)$ represents the cost (in e.g. \$/unit) as a function of cumulative experience (in units). The exponent α determines the rate of cost reductions and is frequently expressed using the so-called progress ratio. An 80% progress ratio ($PR = 0.8$) means that costs are reduced to 80% of the previous level for each doubling of cumulative experience. The constants C_0 and E_0 fix a starting point for the curve.

Note that this formulation is capable of representing the two salient properties of learning according to Arrow (1962):

- Learning is the product of experience. Learning can only take place through the attempt to solve a problem and therefore only takes place during activity.

- Learning associated with repetition of essentially the same problem is subject to sharply diminishing returns.

The first statement is simply the assertion that the relevant independent variable is not time, but experience. The second statement is represented in the experience curve by virtue of its exponential form; i.e. the first 100 units produced lead to greater cost reductions than subsequent production of 100 units.

The rate of cost reduction varies significantly between technologies, with typical progress ratios ranging from 65% to 95% (Ayres and Martinàs 1992, Argote and Epple 1990, Christiansson 1995). Regarding energy supply options, Neij (1997, née Christiansson) distinguishes between large-scale technologies, e.g. coal combustion and nuclear power, small-scale technologies, e.g. gas turbines and wind power, and modular technologies, e.g. photovoltaics and fuel cells. Whereas large-scale plants have shown constant or increasing costs ($PR \geq 100\%$) due to improved efficiency, safety and environmental performance, small-scale plants show a progress ratio around 87% (gas turbines), and modular technologies have progress ratios averaging 80%.

Christiansson (1995) also stresses that the learning rate may change over time. Experience curves often display two separate phases with different progress ratios. Ayres and Martinàs (1992) 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.

Ayres and Martinàs emphasize that the experience curve relation cannot hold forever: "Once the later stages of the life cycle are reached, both product technology and production technology tend to become standardized. At this point learning ceases to be related directly to production experience, and costs do not continue to decline (in a predictable way)."

A numerical example

A simple numerical example based on the experience curve for photovoltaic modules in figure 4 may now prove illuminating. We set the experience curve parameters to:

PV module cost (1993): C_0 = 6 \$/W_P
cumulative experience (1993): E_0 = 300 MW
progress ratio: PR = 0.82

We extrapolate the experience curve to C = 1 \$/W_P, a level at which photovoltaics may begin to compete with conventional baseload electricity. This cost level corresponds to a cumulative experience of 157 GW_P. In other words, once 157 GW_P of modules[3] have been produced/installed, costs should reach the 1 \$/W_P level. With a straightforward integration[4] of the experience curve relation, the total cost of producing this amount of PV modules is seen to be 217 G\$. Averaging this sum over the required module

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[3] How much is 157 GW_P? Assuming a reasonably favorable average yearly solar insolation of 200 W/m^2, we obtain 275 TWh, or roughly double Sweden's current electricity production.

[4] Total cost $= \int_{E_0}^{E} C(E)\,dE = \frac{1}{1-\alpha}\left(E \cdot C(E) - E_0 \cdot C_0\right)$

production results in an average cost less than 1.4 $/W_P$! Such is the magic of the exponential function...

This simplified analysis would seem to imply that, assuming we believe in the continuation of the experience curve, we should not delay investing heavily in electricity production from PV as well as the PV module manufacturing industry. However, the analysis also raises a number of questions:

Is this scenario plausible considering competition from established technologies? Or perhaps competition from other emerging, swiftly developing technologies? How fast can PV penetrate into the energy system? Does the penetration require retirement of existing capacity? Is this kind of "forced" technological development profitable? Does it depend greatly on discount rates? Is it an efficient greenhouse gas mitigation strategy? How is the scenario affected by uncertainties in fossil fuel prices, or CO_2 emission restrictions? Or uncertainties in the experience curve itself?

It is clear that while experience curves present an intriguing tool for assessing technological development, they must be complemented by other tools suitable for addressing the type of questions above. Energy system models provide this possibility, although conventional models are weak in their treatment of technological development. The marriage of experience curves and energy system models would therefore seem to be a promising new tool for energy policy analysis.

3. GENIE

This chapter is a description of GENIE[5], a model of the <u>G</u>lobal <u>EN</u>ergy system with <u>I</u>nternalized <u>E</u>xperience curves.

Basically, GENIE optimizes long-term choices of electricity generation technologies given assumed future demand for electricity. The model minimizes the total discounted system cost subject to technological and environmental constraints. It differs from most related models by its explicit treatment of technological development using experience curves.

The main purpose of GENIE is to provide qualitative insights into the dynamics of technological development in the energy system. It is not intended as a complete tool for general energy policy analysis.

Other models

There are other efforts involving experience curves within an energy systems modelling framework. Anderson and Bird (1992) 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.

Williams and Terzian (1993) perform a traditional cost/benefit analysis of accelerated global deployment of photovoltaics. Experience curves are used to project future PV costs, and a simple load-curve model is used to estimate the benefit of avoided costs for conventional electricity. Experience curves are not directly included in the model, however.

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[5] 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.

Messner (1997) has independently developed a model very similar to GENIE. Her work is an extension of the well-known MESSAGE linear programming model for energy systems analysis, and includes endogenous experience curves in the same way as GENIE. Comparisons to her model will be made wherever appropriate throughout the remainder of this thesis.

Some speculation as to why there have not been more attempts to combine the benefits of energy systems optimizing models and experience curves may be in order[6]. The main reason is very likely the expected computational difficulty of solving a combined model, see below. Non-convex optimization of large models was widely considered impossible not many years ago, but swift development of computers and algorithms has recently made this possible.

Overview

GENIE models long-term development of the global electricity system, spanning the years 1995-2075 with eight 10-year time periods.

The model features four major world regions, North, South, West and East, as shown in figure 5. The regions reflect differences in seasonal electric load, expected future growth of electricity demand and availability of natural resources such as natural gas, solar insolation and hydropower.

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[6] Note added in proof: the MERGE and PRIMES models have very recently been modified to include experience curves.
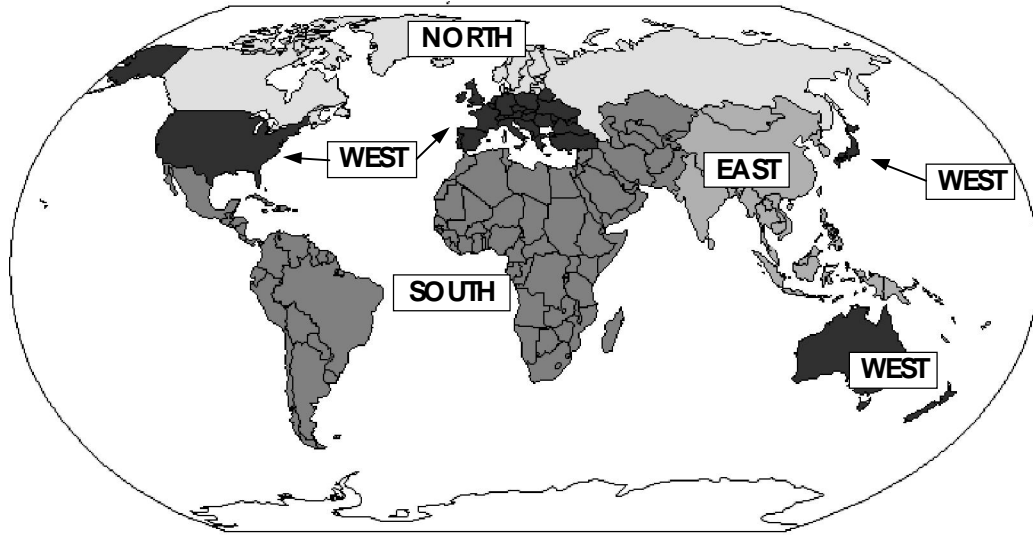
FIGURE 5   The four world regions in GENIE.

There are currently twelve technological options for electricity generation in GENIE. These are conventional coal-, gas- and oil-fueled power plants, conventional gas turbines fueled by oil, hydropower, nuclear power, advanced coal power, combined cycle gas turbines (CCGT), fuel cells fueled by natural gas, wind power, photovoltaic solar cells (PV) and a combined photovoltaic-hydrogen technology (PV-H2). The technologies are intended to be generic: for instance, advanced coal power includes both pressurized fluidized bed and integrated gasification combined cycle technologies, and photovoltaics could indicate both silicon wafer and thin-film alternatives.

Wind power and PV are purely intermittent, whereas the combination technology PV-H2 is non-intermittent. The latter consists of PV, electrolysis of water into hydrogen and oxygen, storage of H_2 and O_2, and recombination of H_2 and O_2 in fuel cells.

Technology investment costs are determined endogenously in the model by experience curves. To minimize computational difficulty, only technologies with a large potential for experience-based cost reduction are treated by experience curves. These are currently: advanced coal power, CCGT, wind power, fuel cells, PV and PV-H2. Other technologies are considered established with constant investment costs.

GENIE is solved assuming perfect foresight, with the objective to minimize total discounted costs for the global electricity system. Information about technologies is assumed to flow freely between regions with no delay. Therefore, technology characteristics are identical in all regions, and each technology is described by one global experience curve. Each region is viewed as a large electric grid, with its own requirements for peak and reserve capacity.

Activities in the energy system outside the electric system are not described, but non-electric demands for fossil energy resources are included in the model. This is necessary to generate internally consistent fuel prices. GENIE requires exogenous scenarios for the time development of regional demands of electricity and non-electric fossil fuels.

A schematic representation of internal and external elements of GENIE appears in figure 6 (c.f. figure 1).

Anatomy of a GENIE

This section highlights some significant elements of the model implementation, except those concerning experience curves, which appear in the next section.

GENIE is written in AMPL, a language for mathematical programming similar to GAMS. AMPL has an intuitive syntax, so the model should be intelligible for a reader with experience of mathematical programming. For reference, the complete model listing is included in Appendix C.

There are only two (generic) independent variables in GENIE: electricity generation (`electricity`) and new capacity investments (`invest`). These are both indexed over all technologies, regions and time periods. All other variables, e.g. `capacity`, `fuel_use`, `co2_emissions` and `cost` are ultimately defined as functions of `electricity` and `invest`.
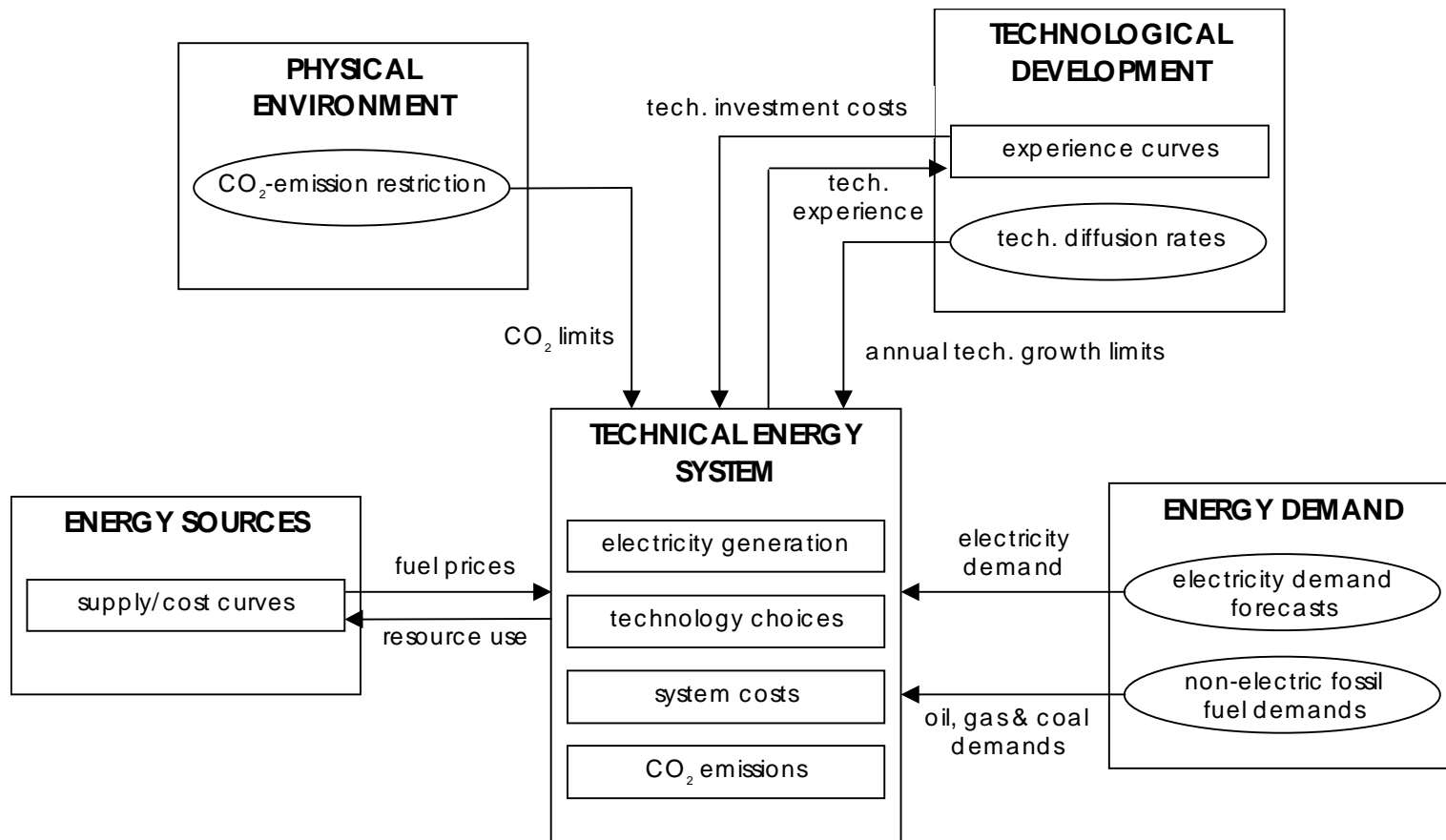
FIGURE 6   Internal and external elements of GENIE. Endogenous components shown with rectangles and exogenous components with ovals.

The basic model relations are (excluding pure definitions):

Energy balance:
>   Electricity generation must exceed demand.

Capacity limitation:
>   Electricity generation is limited by installed capacity.

Peak & reserve requirements:
>   "Extra" capacity is required for peak and reserve demands.

Growth restriction:
>   Technologies are subject to a simple annual growth limit.

Expansion potential:
>   Regional wind- & hydropower resources are limited.

Intermittent generation limits (individual and collective):
>   Solar and wind cannot supply all electricity alone.

CO_2-emissons limit:
>   Total CO_2-emissions from electricity can be limited.

Fossil fuel supply/cost relation:
>   Fossil fuel costs increase as resources are depleted.

The last relation implies that fossil fuel costs are determined endogenously in GENIE using supply/cost-curves. This is another non-linearity, but, in contrast to experience curves, it is convex. It therefore lends itself fairly easily to an implementation using piecewise-linear approximations.

Late investments are salvaged in the model; i.e. compensation is given for plants with remaining lifetime in the final time period. This is necessary, because otherwise the model would stop investing as it approaches "the end of the world".

In the pilot version of GENIE described in the enclosed paper, each time period was divided into 6 seasons. The reason for this was mainly to account for regional load curve variations. The seasons were subsequently removed since they complicated the model unnecessarily. Instead, load curve effects are now accounted for by using availability factors, which differ across regions for some technologies (e.g. PV).

Internalizing experience curves

General

It has been noted that the introduction of experience curves in energy systems models, though desirable, leads to non-convex minimization problems that can only be solved with considerable difficulty. Experience curves feature increasing returns to scale, which causes computational complexity by generating multiple local optima. The high dimensionality of the problem also contributes to the formidable task of proving that the global optimum has been found.

Experience curves can be implemented in two conceptually different ways:

- by retaining the continuous non-linear experience curve formulation and solving using modern algorithms for global optimization, or

- by making piecewise-linear approximations of the experience curves, using integer variables as segment indicators and solving with the well-established branch-and-bound method for mixed-integer programming (MIP).

The first approach was used during the pilot phase of GENIE (see enclosed paper), but using conventional non-linear programming instead of global optimization methodology. This alternative is very simple to implement and solves rapidly to a local optimum, but the global optimum cannot be proved. Many model runs from different starting-points are therefore necessary to satisfy the user that the global optimum has indeed been found. Global optimization methods have not been tested since they are not yet available in commercial optimizers. Solution times using these methods would probably be of the same magnitude as those in the MIP-alternative.

The second approach is the one currently used in GENIE, as well as by Messner (1997). The great advantage of this method is the guarantee of finding the global optimum. However, the implementation is more complicated than the previous method (see the next section) and solution times are several orders of magnitude larger than for corresponding linear programs. Solution

time increases dramatically with the number of experience curves and the number of time periods in the model.

In contrast to GENIE, Messner (1997) assumes that learning by experience has an ultimate limit. I.e., after reaching a certain level, investment costs cease to decline. This represents a fundamentally different view than GENIE, which is based on the assumption that investment costs do not cease to decline *as a function of experience*. However, as a technology saturates the market, progressive doublings of experience become increasingly scarce, so investment costs stabilize of their own accord.

Piecewise-linear implementation

A straightforward piecewise-linearization of specific investment costs along the experience curve would not result in a linear model, since specific costs (measured in $/kW) must be multiplied with new capacity investments (in kW) in the cost function. Instead, the function to be approximated by linear segments is the cumulative investment cost curve, i.e. the integral of the experience curve (calculated in footnote 4, chapter 2). This ensures a linear cost function.

Several alternative formulations were tested; two of which had a significant performance advantage over the others. The simplest, from Floudas (1995), appears below. The other method relates segment indicators across time and may be the most efficient for problems with more time periods. For more information, contact the author.

Suppose a three-segment approximation is to be used. Let x denote the experience variable and C(x) the cumulative investment cost approximation. Also, let x_i and c_i be the segment breakpoints, see figure 7. The linear segments can be written:

$$C(x) = \begin{cases} \alpha_1 + \beta_1 \cdot x & \text{for} & x_1 \le x \le x_2, \\ \alpha_2 + \beta_2 \cdot x & \text{for} & x_2 \le x \le x_3, \\ \alpha_3 + \beta_3 \cdot x & \text{for} & x_3 \le x \le x_4, \end{cases}$$

where the constants α_i and β_i are easily determined from the breakpoints x_i and c_i. Next, introduce binary variables δ_i and continuous variables λ_i. The entire implementation can now be written in Greek:

$$\begin{cases} C(x) = (\alpha_1 \cdot \delta_1 + \beta_1 \cdot \lambda_1) + (\alpha_2 \cdot \delta_2 + \beta_2 \cdot \lambda_2) + (\alpha_3 \cdot \delta_3 + \beta_3 \cdot \lambda_3) \\ x = \lambda_1 + \lambda_2 + \lambda_3 \\ x_1 \cdot \delta_1 \le \lambda_1 \le x_2 \cdot \delta_1 \\ x_2 \cdot \delta_2 \le \lambda_2 \le x_3 \cdot \delta_2 \\ x_3 \cdot \delta_3 \le \lambda_3 \le x_4 \cdot \delta_3 \\ \delta_1 + \delta_2 + \delta_3 = 1 \\ \delta_1, \delta_2, \delta_3 = [0,1] \end{cases}$$

or in quasi-English:

If $\delta_1 = 1$, then $\delta_2 = \delta_3 = 0$, which forces $\lambda_2 = \lambda_3 = 0$, therefore $x = \lambda_1$, $x_1 < x < x_2$, and finally $C(x) = \alpha_1 + \beta_1 * x$.
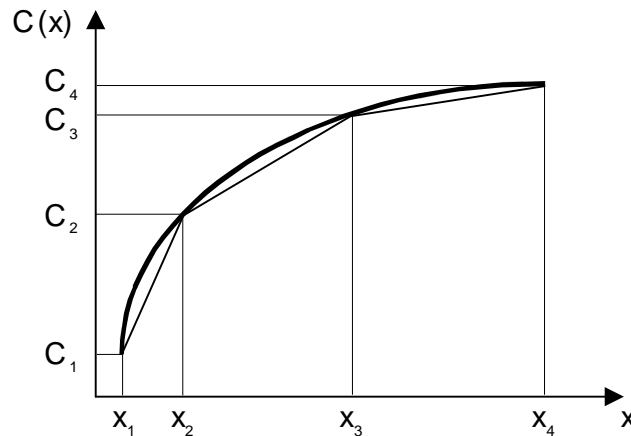

FIGURE 7   Segmentation of the experience curve.

Accuracy of the piecewise linear approximation

Due to the concavity of the experience 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 of the experience curves: 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

Since computational complexity is such an obvious criticism to internalizing experience curves, much effort has been placed in improving efficiency of the implementation. Some experiences are shared here.

Williams (1990) gives a general recommendation for MIP-models that imposing "unnecessary" constraints on the integer variables may improve performance. Two extra constraints on segment indicator variables based on the observation that experience must increase over time were therefore added to GENIE. Significant reductions of solution time were observed after this change. This improvement can probably be attributed to a refined (i.e. tighter) LP-relaxation[7].

Several attempts at introducing so-called special ordered sets (SOS) of variables were made. 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

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[7] 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.

performance improvement was observed in GENIE. 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 seems to cause performance degradation.

The MIP-solver currently used for GENIE, CPLEX 4.0, has several parameters that can be modified to change the behavior of the solver. One parameter is worth mentioning, since changing it from its default value reduced both solution times and memory requirements by an order of magnitude. The parameter, `varsel`, was changed to `strong branching`. 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 is apparently worth the extra effort.

Also, with `varsel = strong branching`, CPLEX generally converged much faster to the final solution. In other words, even the first local optimum found was very similar to the global optimum. This seems to suggest that it would be possible to interrupt the solver after a relatively short time, and still be confident of terminating with a very good solution. This was not the case with other parameter settings, as the solution could change fairly dramatically near the end.

The complexity of GENIE, as measured by the amount of time, nodes and iterations required to reach the solution, was generally very problem dependent. The "obviousness" of the optimum is what primarily determines how difficult a problem is, not problem size or number of integer variables as might be expected. I.e., a problem with several structurally different solutions but nearly identical costs might need extremely many iterations to solve, while another problem with a clear-cut optimum would be solved relatively swiftly. For example, complete solution times for the model runs in the next chapter varied between 2 and 107 hours. Similar sized linear programs were solved in seconds.

4. Application

This chapter demonstrates the use of GENIE for assessing emerging energy technologies. The application is basically identical to the pilot study in the enclosed paper. The main differences are an updated input database, the addition of two new technologies (wind power and conventional gas turbines), and the number of technologies with experience curves (increased from two to six). Also, the model itself has changed since the pilot study, see the previous chapter for details.

In spite of these fairly extensive changes, the main observations and conclusions remain the same. This gives some confidence in the basic model dynamics.

Input data and assumptions

Data sources

For reference, the input database is included in the model printout in Appendix C.

Electricity demand and non-electric fossil fuel demand are determined by exogenous assumptions of future development in each region. The demands are assumed to grow exponentially at rates based on scenarios from the U.S. Energy Information Administration (EIA 1996), the International Atomic Energy Agency (IAEA 1991) and IIASA/WEC (1995).

All data on the current global energy system, e.g. electricity generation by technology, installed capacity, non-electric fossil fuel use, etc., was obtained from the EIA (1995).

Technology performance and cost data, e.g. lifetime, efficiency, operating & maintenance costs and investment costs were compiled from the Energy Technology Support Unit (ETSU 1994), the Intergovernmental Panel on Climate Change (IPCC 1996) and the Swedish MARKAL database (Nyström and Andersson 1995). Also, recent investment costs from ongoing construction projects

around the world were found in several issues of the Financial Times Energy Economist Briefings (1996-97).

Assumptions

All four non-renewable fuels in GENIE, coal, natural gas, oil and uranium, have costs determined endogenously by supply/cost curves. However, oil and uranium are assumed to have a global market, i.e. costs depend on total global resource use and are identical for all four world regions. In contrast, coal and natural gas are considered to be regional resources, with costs determined by fuel use in each region. The supply/cost curves used are based on Rogner (1996), while current fuel cost data was again obtained from the EIA (1995).

Fuel use in excess of current proven reserves is allowed by the model, but is discouraged by increasing fuel costs. Natural gas can be freely traded between regions North and West, but no other fuel trade is allowed.

Technological growth rates are currently limited to 30% per year in GENIE. This may seem overly optimistic in view of the large inertia of the energy system. Most major historical transitions (e.g. wood to coal, coal to oil) occurred at expansion rates that seldom exceeded 10% a year. However, both gas turbines and nuclear power have sustained growth rates of 30%, so this high level may be a reasonable upper limit after all. Still, some form of logistic growth (featuring declining growth rates) might be appropriate for future implementation, but this was not considered to be worth the extra effort in this demonstration application.

Technological progress ratios, i.e. "learning rates" of experience curves, are naturally of central importance for this study. Following general characterizations from Neij (1997), the modular technologies PV, PV-H2 and fuel cells were assumed to have the steepest progress ratios (0.82, 0.85 and 0.85 respectively), the small-scale technologies CCGT and wind power slightly less steep ratios (both 0.88), while the large-scale technologies display little (advanced coal, 0.95) or no experience-based learning (all others).

A trade-off between solution time and accuracy determines the choice of segmentation of experience curves. Approximations of six

segments were used for all technologies except PV and PV-H2, which were allocated ten and eight segments respectively.

The discount rate was set to 5% for the model runs appearing in the next section. This level is typical for energy systems models and can be viewed as "conventional wisdom". However, discount rate choices often have a critical impact on model results. Also, it has been argued that the rate cannot be determined on objective grounds, but is ultimately a question of value judgements (Azar 1995). Therefore, alternative runs using a lower discount rate of 2% were also performed, see Appendix B. This value was obtained by setting the social rate of time preference to zero and expected future economic growth to 2%.

Results

Results were produced for two scenarios, a base scenario and a scenario with limited CO_2-emissions. All optimizations were performed for a time horizon reaching to 2075, but only results to 2055 are reported[8]. This is done in an attempt to "salvage learning" in GENIE. Otherwise, the model would be blind to benefits of technological development that occur after the final time period.

Base scenario

The first solution to the base scenario appears in figure 8. It can be described as a business-as-usual development of the global electricity system, with total system costs amounting to 9117 billion US$. In this solution, the conventional fossil technologies are phased out and initially replaced by CCGT and hydropower. Later, possibly due to increased gas prices, CCGT is replaced by advanced coal power, which eventually becomes the dominant technology of the system. Wind power makes a significant contribution to the global electricity balance and nuclear power is revived after an initial decline to become the second largest source

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[8] The figures appear to end at 2045, but all time periods have a length of ten years.

of electricity. CO_2-emissions from this system roughly double by the middle of the next century as compared to 1995 levels.

Although invisible in figure 8, the model continually invests in significant amounts of conventional gas turbines in order to satisfy demands for reserve and peak capacity (the same happens in all model runs).

A completely different solution to the same scenario appears in figure 9. This alternative has a total system cost of 9106 billion US$, marginally lower than the previous cost, and is the true optimal (least cost) solution. This case is initially similar to the previous one, except that CCGT has a less prominent role. After 2015, however, the two cases diverge. In case 2, fuel cells swiftly gain market shares and eventually become the largest source of electricity. This development occurs at the expense of CCGT, advanced coal and nuclear power. Also, photovoltaic solar cells (PV) contribute 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 later reduced below 1995 levels.

It should be emphasized that these alternative futures stem from the same scenario, i.e. input databases and assumptions are identical for both cases. The lower costs, lower emissions and increased technological diversity of case 2 suggest that this path can be viewed as a no-regrets policy, making it the preferred choice for decision-makers. But the choice must be made early: in case 1, there are no investments in PV or fuel cells. In case 2, these technologies grow at maximum speed from the first time period onward. During the first decades, these investments are not profitable, but they are necessary to ensure future (greater) profitability. This situation is

Base scenario, case 1

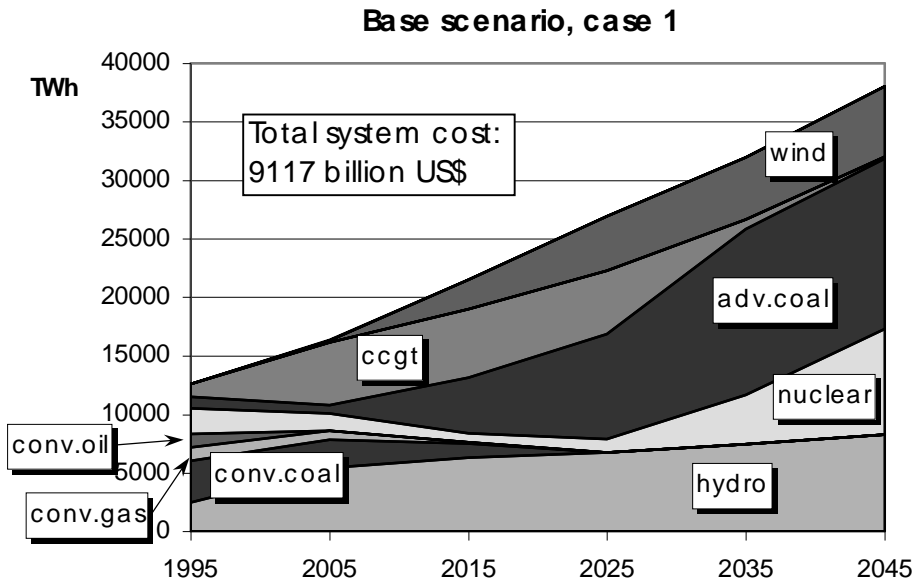**FIGURE 8**   Global electricity generation by technology in the base scenario: case 1, a business-as-usual situation.

Base scenario, case 2
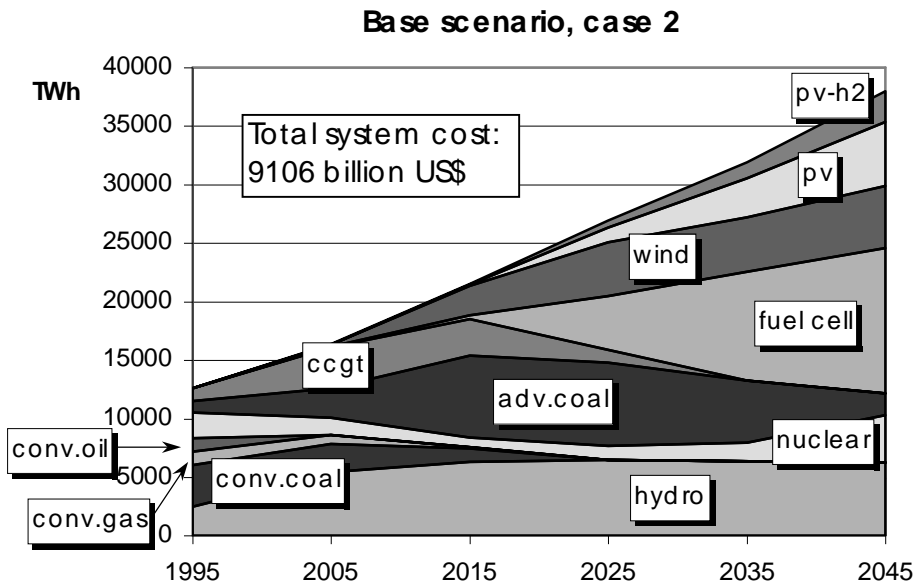
FIGURE 9   Global electricity generation by technology in the base scenario: case 2 (optimal), a more diverse system.

Annual investment costs, base scenario
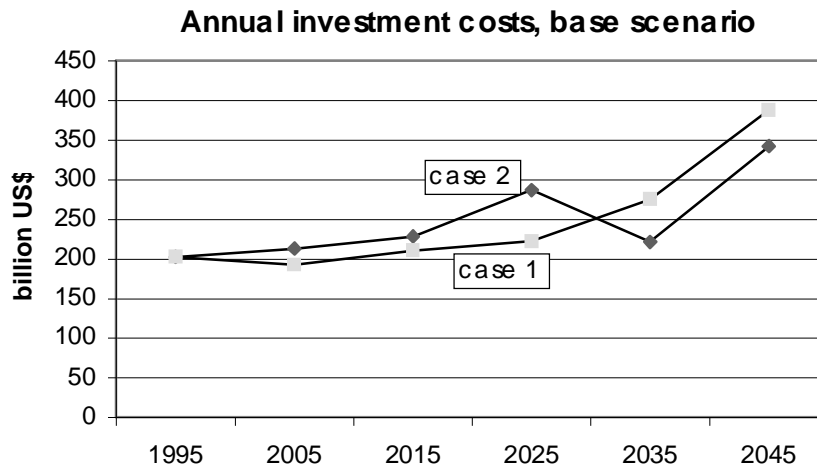
FIGURE 10   Annual investment costs for the base scenario.

illustrated in figure 10, which shows annual investment cost profiles for the two solutions.

This figure emphasizes the risk of technology lock-in. Case 2 requires approximately 30% more investment capital than case 1 in the year 2025. 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, the business-as-usual future. There will then be no opportunity to gather cost-reducing experiences with emerging technologies because they will be effectively locked-out by established technologies.

However, implicit in the model representation is the assumption that large grid-connected electricity systems will bear the costs of introducing the emerging technologies. In practice, nursing- and bridging markets with a greater willingness-to-pay than the final mass market may provide a natural growing ground for the emerging technologies. The burden of technology development on the grid-connected systems may then be eased and lock-in prevented.

Another result from GENIE is the time development of investment costs due to experience effects, see table 1. For comparison, investment costs for other technologies in GENIE are: hydro 2500 $/kW, nuclear 2500 $/kW, conventional coal 1300 $/kW,

conventional oil 800 $/kW, conventional gas 750 $/kW and gas turbines 400 $/kW.

	1995	2005	2015	2025	2035	2045
adv.coal	1400	1330	1239	1176	1176	1176
ccgt	800	678	678	678	678	678
fuel cell	4500	2256	1217	892	651	600
wind	1200	852	531	420	420	387
pv	7000	3514	1509	715	593	418
pvh2	8193	4223	2040	1031	819	637

TABLE 1   Time development of investment costs ($/kW) for technologies with experience curves in the base scenario, case 2.

A comparison of the optimal solution (case 2) with Messner's (1997) model runs shows that the two models produce very similar results. The discrepancies can be directly attributed to differences in the technology databases. For instance, advanced nuclear power makes a large contribution in Messner's model, but this technology is not included in GENIE. For fuel cells, the situation is the reverse. Relative contributions from other technologies are essentially identical.

So far, only results on a global scale have been presented. But the global totals hide large regional differences. Electricity generation in case 2 for the four world regions can be found in Appendix A.

Limited CO_2-emissions scenario

In the second scenario, a limit was placed on accumulated emissions of CO_2. This "total CO_2-budget" was fixed at 292 Gton CO_2, corresponding to 50 years of emissions at the current level. Since the model horizon is 80 years, this restriction is severe. The purpose of this construction is to produce insights into the timing of CO_2-mitigation efforts.

The results of the GENIE model runs appear in figures 11 and 12. Again, two local optima are observed, but the cases only differ by the replacement of nuclear power with PV-H2 in case 2. The value

of the emerging technologies PV and fuel cells is much higher in the limited CO_2-emissions scenario, and consequently both technologies are developed as quickly as possible in both cases. There is not much room for coal power in this scenario, but the CO_2-efficient fossil technologies CCGT and fuel cells are used to a large extent. Total system costs are 9232 billion US$ for case 1 and 9489 billion US$ for case 2. It is interesting to note that demanding limits on CO_2-emissions are possible at a cost increase of only slightly more than 1%. The corresponding figure for a system without nuclear power is 4%.

CO_2-emissions for both the base scenario and the limited CO_2-emissions scenario are shown in figure 13 (case 2 of the limited CO_2-emissions scenario is omitted, since its emissions are virtually identical to case 1).

The implications to the timing of CO_2-mitigation efforts can be summarized as follows. A swift expansion of CCGT can enable emissions to be retained at current levels until 2015, after which the emergence of new technologies should allow steady emission reductions. But development efforts and hence investments in new low- CO_2 technologies must begin immediately.

Limited CO2-emissions scenario, case 1

TWh

Total system cost:
9232 billion US$

Labels on chart: pv-h2, pv, wind, fuel cell, ccgt, adv.coal, nuclear, conv.oil, conv.coal, hydro, conv.gas

Y-axis: 0, 5000, 10000, 15000, 20000, 25000, 30000, 35000, 40000
X-axis: 1995, 2005, 2015, 2025, 2035, 2045
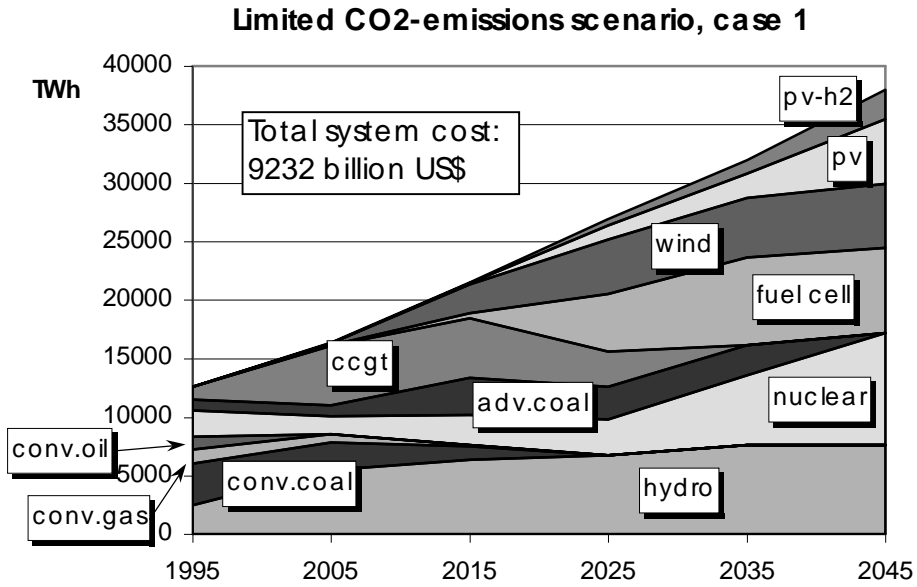
FIGURE 11   Global electricity generation by technology in the limited CO$_2$-emissions scenario: case 1.

Limited CO2-emissions scenario, case 2

TWh

Total system cost:
9489 billion US$

Labels on chart: pv-h2, pv, wind, fuel cell, ccgt, nuclear, adv.coal, conv.oil, conv.coal, hydro, conv.gas

Y-axis: 0, 5000, 10000, 15000, 20000, 25000, 30000, 35000, 40000
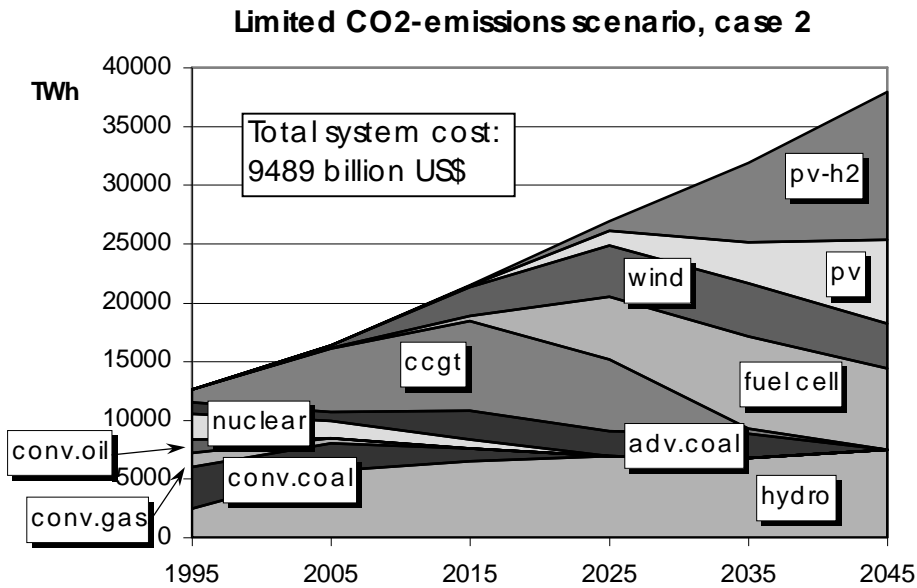X-axis: 1995, 2005, 2015, 2025, 2035, 2045

FIGURE 12   Global electricity generation by technology in the limited CO$_2$-emissions scenario: case 2.

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Annual CO$_2$-emissions

base scenario, case 1

base scenario, case 2

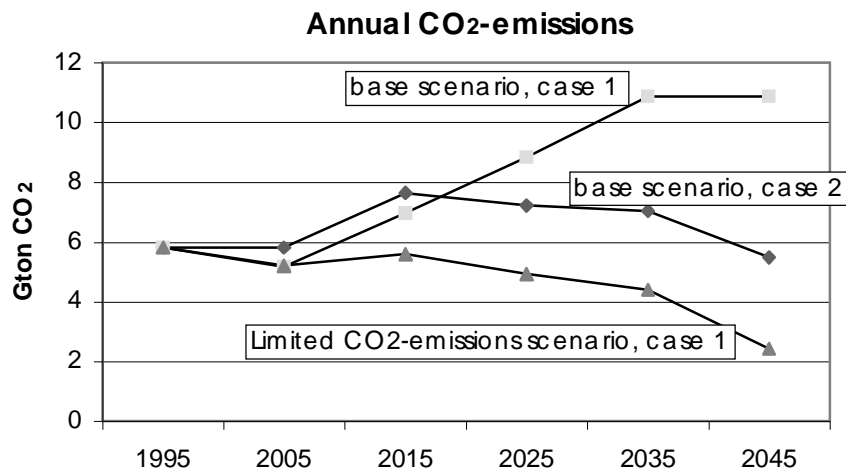Limited CO2-emissions scenario, case 1

FIGURE 13   Annual CO$_2$-emissions in the two scenarios.

5. Conclusions

Energy systems models are important tools for energy policy analysis and have an essential role in the integrated assessment of climate change. However, most models are unable to consider prospects of technological development adequately, and may therefore underestimate potential of emerging technologies such as photovoltaic solar cells and fuel cells.

The purpose of the research leading to this thesis has been to investigate whether it is possible to improve model treatment of technological development by internalizing experience curves.

The main findings can be summarized as follows:

- The GENIE model demonstrates that the internalization of experience curves is now a feasible methodology for handling induced technological development in dynamic energy systems models.

- The non-convex experience curves cause considerable computational difficulty. However, the mixed-integer implementation using piecewise-linear approximations of experience curves enables the model to find and prove the global optimum. Some implementation "tricks" can reduce solution times by several orders of magnitude.

- Qualitatively new modelling insights are provided by GENIE, such as the existence of alternative futures at similar costs, emphasizing the risk of technological lock-in. Results also indicate increased capital requirements for starting learning-intensive investment paths.

A synthesis of the literature survey and lessons learned from GENIE has several implications to energy policy:

Technological development does not occur autonomously, but is induced by market-related pressures. To ensure the development of emerging technologies, a balance of technology push and market pull is required. A government can enhance the former by financing R&D and the latter by market support efforts such as

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investment subsidies, tax exemptions or attractive loans. The importance of market pull is often underestimated.

Experience is a prerequisite for technological development. Continuous investments in emerging technologies are therefore necessary for consequential improvements. Considering the inertia of energy systems, these investments must begin now if the technologies are to contribute significantly to the energy system 30 years into the future.

GENIE illustrates the insights from the literature survey. Plausible locally optimal solutions show deviating paths leading to drastically different future energy systems. Timely support of emerging technologies is probably necessary to avoid lock-in of established technologies and build a diverse, flexible energy system. This is a no-regrets policy.

Future work

A natural continuation of this research project involves addressing an inherent weakness of experience curve methodology, namely the assumption that future learning rates are known with certainty. GENIE will therefore be extended to include internalized uncertainty of learning rates, implemented using stochastic programming.

Acknowledgements

I would like to express my gratitude to my advisor, Professor Clas-Otto Wene, for his enthusiastic support of my work and for the inspiration to launch a research project on modelling learning curves in the first place.

My colleagues deserve mention for creating such a friendly work environment, and scrumptious cakes.

And a special thanks to my family and friends for all the things that really matter. See you at the party!

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Appendix A

This appendix contains additional GENIE results for the base scenario, case 2. Electricity generation for each of the four world regions is shown, c.f. figure 9 for the corresponding global total. The figures appear overleaf, without comment. (The discount rate is 5%, as in chapter 4.)

Region West (base scenario, case 2)

TWh

pv-h2

pv

wind

ccgt

conv.oil

nuclear

fuel cell

conv.gas

adv.coal

conv.coal

hydro

18000
16000
14000
12000
10000
8000
6000
4000
2000
0

1995　2005　2015　2025　2035　2045
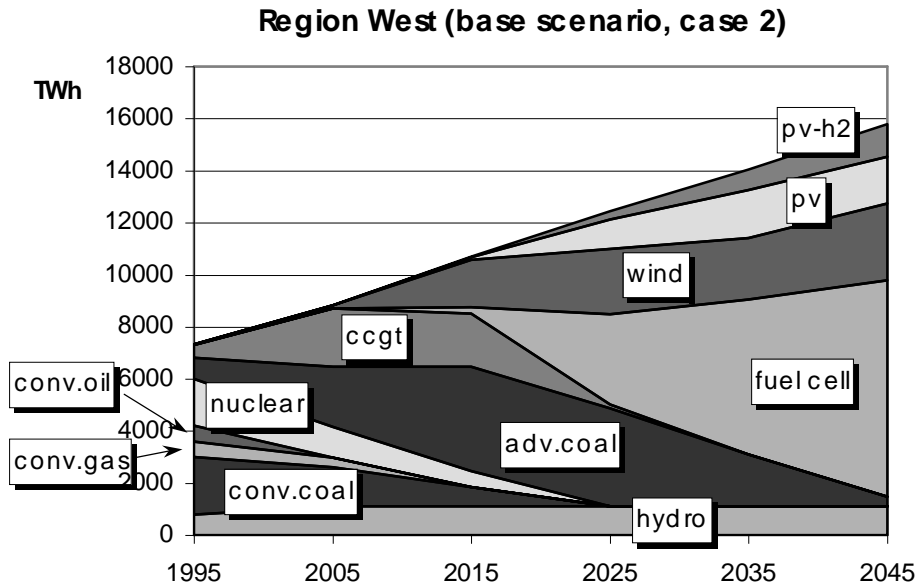
FIGURE 14　Global electricity generation by technology in region West (base scenario, case 2).

Region North (base scenario, case 2)

TWh

pv-h2

pv

wind

ccgt

adv.coal

nuclear

conv.fossil

hydro

4500
4000
3500
3000
2500
2000
1500
1000
500
0

1995　2005　2015　2025　2035　2045
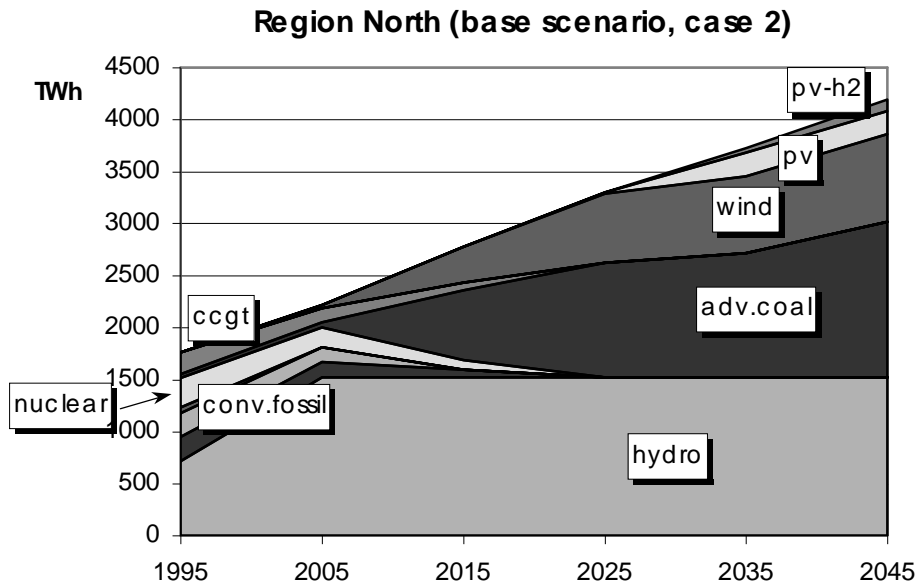
FIGURE 15　Global electricity generation by technology in region North (base scenario, case 2).

A:2

Region East (base scenario, case 2)

TWh

14000
12000
10000
8000
6000
4000
2000
0

pv-h2
pv
wind
fuel cell
adv.coal
nuclear
ccgt
conv.oil/gas
conv.coal
hydro

1995   2005   2015   2025   2035   2045
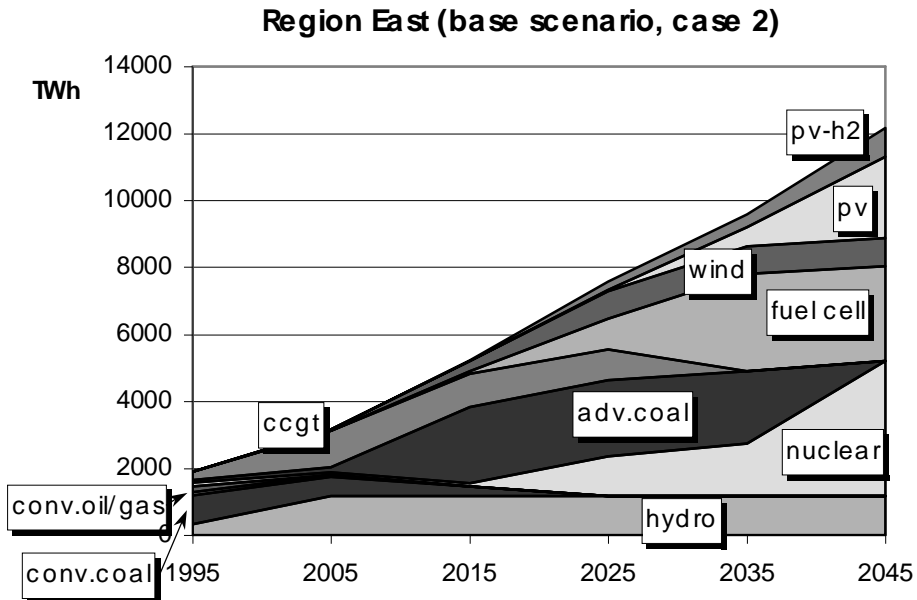
FIGURE 16   Global electricity generation by technology in region East (base scenario, case 2).

Region South (base scenario, case 2)

TWh

7000
6000
5000
4000
3000
2000
1000
0

pv-h2
pv
wind
fuel cell
conv.tech.
hydro

1995   2005   2015   2025   2035   2045
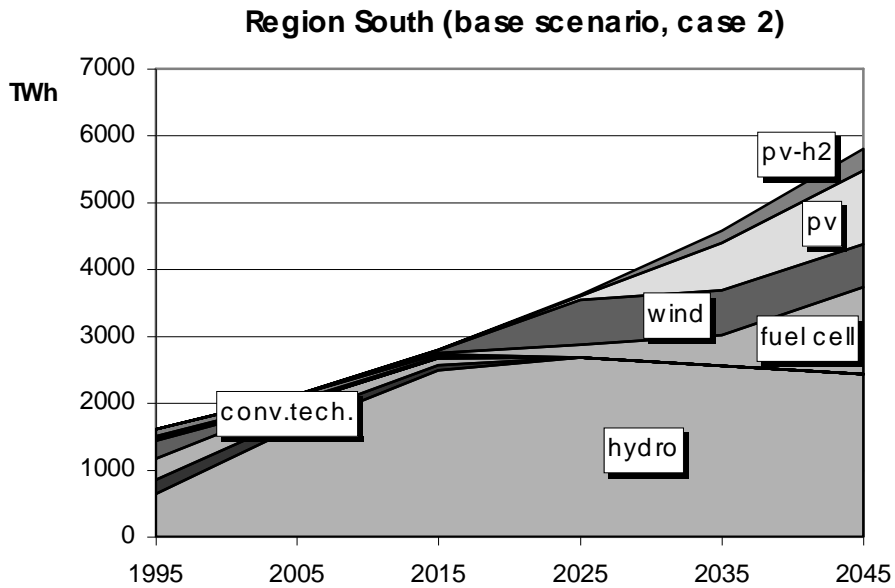
FIGURE 17   Global electricity generation by technology in region South (base scenario, case 2).

A:3

A:4

Appendix B

This appendix contains alternative GENIE runs using a discount rate of 2%. All other input data is unchanged, see chapter 4. The figures appear overleaf, without comment.

Base scenario, case 1
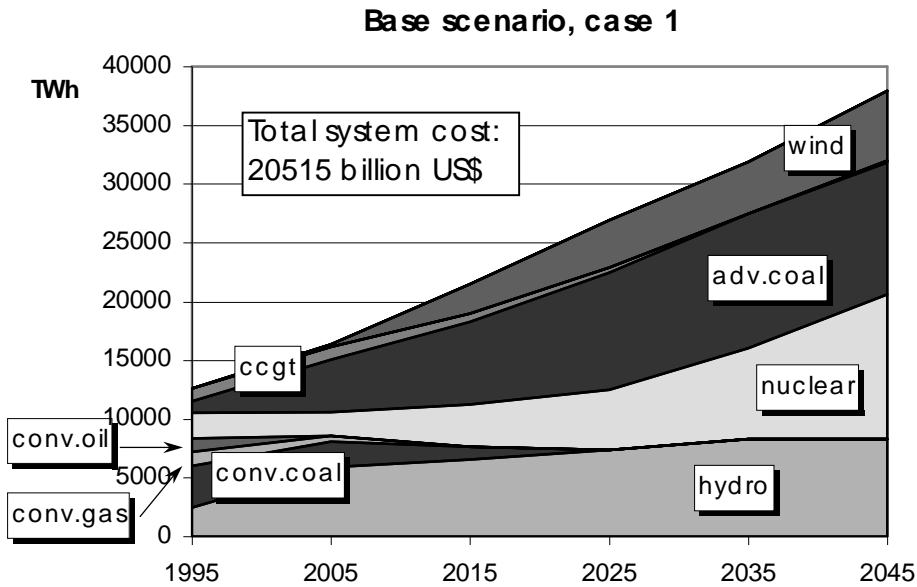
FIGURE 18   Global electricity generation by technology in the base scenario, case 1 (discount rate = 2%).

Base scenario, case 2
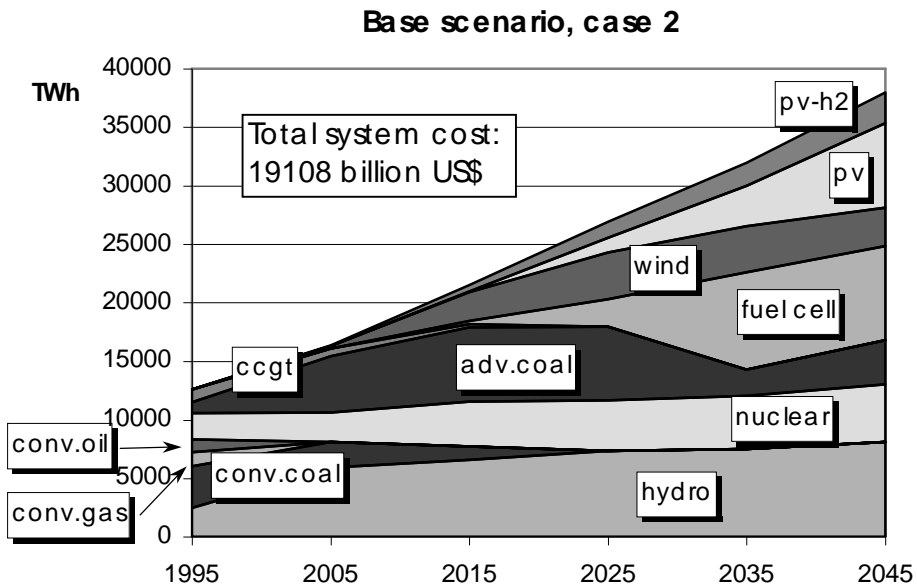
FIGURE 19   Global electricity generation by technology in the base scenario, case 2 (discount rate = 2%).

Limited CO2-emissions scenario, case 1

Total system cost:
19412 billion US$

pv-h2
pv
wind
fuel cell
adv.coal
ccgt
nuclear
conv.oil
conv.coal
hydro
conv.gas

TWh
40000
35000
30000
25000
20000
15000
10000
5000
0

1995   2005   2015   2025   2035   2045

FIGURE 20   Global electricity generation by technology in the limited
CO_2-emissions scenario, case 1 (discount rate = 2%).

Limited CO2-emissions scenario, case 2

Total system cost:
21274 billion US$

pv-h2
wind
pv
ccgt
adv.coal
fuel cell
nuclear
conv.oil
conv.coal
hydro
conv.gas

TWh
40000
35000
30000
25000
20000
15000
10000
5000
0

1995   2005   2015   2025   2035   2045

FIGURE 21   Global electricity generation by technology in the limited
CO_2-emissions scenario, case 2 (discount rate = 2%).

Appendix C

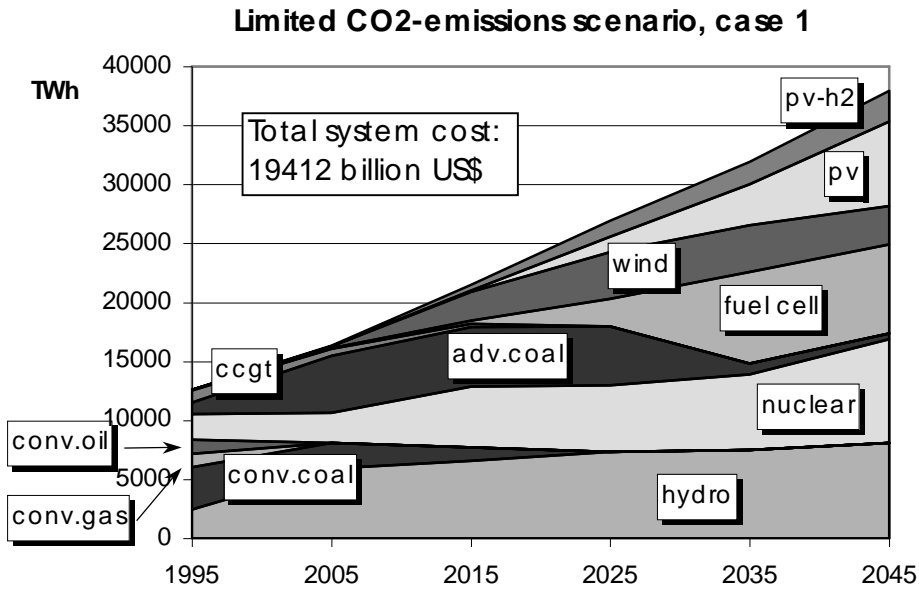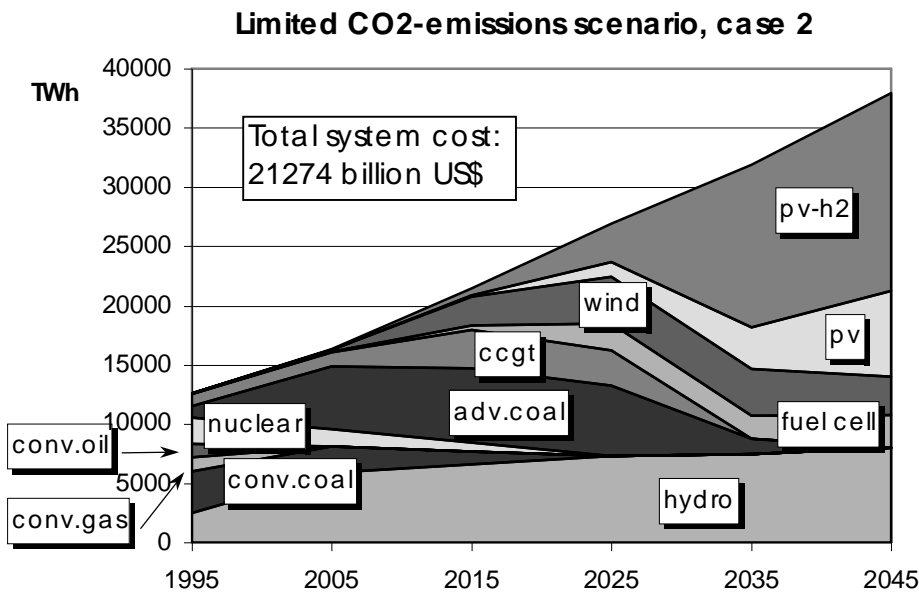This is a printout of the GENIE model. The model equations and input database appear separately.

genie.mod

```
set TECH;
set FUEL;
set TIME ordered;
set REGION;

param years;       # years per period
param eps;  # small number
param dr;   # discount rate
param market_growth;     # maximum yearly market growth
param max_intermittent; # maximum intermittent energy contribution
param dist_efficiency;   # world consumption/generation
param peak_multiplier;   # later regional
param fuel_tech {FUEL,TECH} >= 0;          # 0,1
param lifetime {TECH} >= 0;                # years
param base_invcost {TECH} >= 0;               # $/kW
param fixed_cost {TECH} >= 0;              # $/(kW*year)
param var_cost {TECH} >= 0;               # $/MWh
param efficiency {TECH} >= 0;             # [0,1]
param progress_ratio {TECH} >= 0;         # [0,1]
param intermittent {TECH} >= 0;               # [0,1]
param start_capac {TECH,REGION} >= 0;      # GW
param demand_start {REGION} >= 0;          # TWh
param demand_growth1 {REGION} >= 0;           # [0,1]
param demand_growth2 {REGION} >= 0;           # [0,1]
param demand_growth3 {REGION} >= 0;           # [0,1]
param savings >= 0;                        # [0,1]
param other_availability {TECH,REGION} >= 0;     # [0,1]
param p1 {FUEL} >= 0;                      # $/MWh
param p2 {FUEL} >= 0;                      # $/MWh
```

```
param fuel_reserves {FUEL,REGION} >= 0;            # PWh
param non_electric_start {FUEL,REGION} >= 0;       # TWh
param non_electric_growth1 {FUEL,REGION} >= 0;     # [0,1]
param non_electric_growth2 {FUEL,REGION} >= 0;     # [0,1]
param non_electric_growth3 >= 0;                   # [0,1]
param fuel_co2 {FUEL} >= 0;                         # ton/MWh
param total_CO2_limit >= 0;                         # Gton CO2
param potential {TECH,REGION} >= 0;                 # TWh
param high_exper {TECH} >= 0;
param max_exper {TECH} >= 0;
param npieces {TECH} >= 0;
param max_fueluse {FUEL} >= 0;
param nfuel >= 0;
param max_cuminvcost >= 0;


param time0 := first(TIME);
param time1 := last(TIME);


param learning_index {k in TECH} := -log(progress_ratio[k]) / log(2);
param demand {r in REGION, t in TIME} :=                    # TWh
  demand_start[r] / dist_efficiency *
     if t < 2020 then (1+demand_growth1[r])^(t-time0)
     else if t < 2050 then
          (1+demand_growth1[r])^(2020-time0) * (1+demand_growth2[r])^(t-2020)
     else (1+demand_growth1[r])^(2020-time0) * (1+demand_growth2[r])^(2050-2020) *
          (1+demand_growth3[r])^(t-2050);
param peak_demand {r in REGION, t in TIME} :=                         # GW
     peak_multiplier * demand[r,t] / 8760 * 1000;
param non_electric_use {f in FUEL, r in REGION, t in TIME} :=         # TWh
  non_electric_start[f,r] *
     if t < 2020 then (1+non_electric_growth1[f,r])^(t-time0)
     else if t < 2050 then (1+non_electric_growth1[f,r])^(2020-time0) *
          (1+non_electric_growth2[f,r])^(t-2020)
     else (1+non_electric_growth1[f,r])^(2020-time0) *
     (1+non_electric_growth2[f,r])^(2050-2030) * (1+non_electric_growth3)^(t-2050);
param start_exper {k in TECH} := sum {R in REGION} start_capac[k,R];
param resid_capac {k in TECH, r in REGION, t in TIME} :=              # GW
                    start_capac[k,r] * max(0, 1-(t-time0)/lifetime[k]);
param availability {k in TECH, r in REGION} := other_availability[k,r];
param salvage {k in TECH, t in TIME} := 1/(1+dr)^(time1-t+years) *
     (1-1/(1+dr)^max(0, t+lifetime[k]-time1-years)) / (1-1/(1+dr)^lifetime[k]);
```

```
param discount := sum {T in 0..years-1} 1/(1+dr)^T;



# The following is a fairly complicated scheme for setting the breakpoints of
# the experience curves so that the segmentation is as efficient as possible.
#
#param bpexper {k in TECH, p in 0..npieces[k]} := #breakpoints
#     start_exper[k]+(max_exper[k]-start_exper[k])*(p/npieces[k]);
#     start_exper[k]*(max_exper[k]/start_exper[k])^(p/npieces[k]);
param firstcuminvcost {k in TECH} :=
     base_invcost[k]*start_exper[k]/(1-learning_index[k]);
param highcuminvcost {k in TECH} :=
     firstcuminvcost[k]*(high_exper[k]/start_exper[k])^(1-learning_index[k]);
param lastcuminvcost {k in TECH} :=
        firstcuminvcost[k]*(max_exper[k]/start_exper[k])^(1-learning_index[k]);
param bpindex {k in TECH} := floor(2/3*npieces[k]);
param bptemp {k in TECH, p in npieces[k]-bpindex[k]..npieces[k]} :=
        if p = npieces[k] then lastcuminvcost[k]-firstcuminvcost[k]
        else (p+bpindex[k]+1-npieces[k])/bpindex[k] *
                     (highcuminvcost[k]-firstcuminvcost[k]);
param bpexper {k in TECH, p in 0..npieces[k]} :=   #breakpoints
  if p <= npieces[k]-bpindex[k]-1 then
    ( (bptemp[k,npieces[k]-bpindex[k]]+firstcuminvcost[k]) /
        base_invcost[k]/start_exper[k]*(1-learning_index[k]) )
         ^ (p/(npieces[k]-bpindex[k])/(1-learning_index[k])) * start_exper[k]
  else ( (bptemp[k,p]+firstcuminvcost[k]) /
        base_invcost[k]/start_exper[k]*(1-learning_index[k]) )
         ^ (1/(1-learning_index[k])) * start_exper[k];
param bpcuminvcost {k in TECH, p in 0..npieces[k]} :=
     if p <= npieces[k]-bpindex[k]-1 then
           base_invcost[k]*start_exper[k]/(1-learning_index[k]) *
           ( (bpexper[k,p]/start_exper[k])^(1-learning_index[k]) - 1 )
     else bptemp[k,p];
param bpinvcost {k in TECH, p in 1..npieces[k]} :=
     (bpcuminvcost[k,p]-bpcuminvcost[k,p-1])/(bpexper[k,p]-bpexper[k,p-1]);
param bpfueluse {f in FUEL, p in 0..nfuel} := p/nfuel*max_fueluse[f];
param bpcumfuelcost {f in FUEL, p in 0..nfuel} :=
     p1[f]*bpfueluse[f,p] + (p2[f]-p1[f])/2*bpfueluse[f,p]^2;
param bpfuelcost {f in FUEL, p in 1..nfuel} :=
   (bpcumfuelcost[f,p]-bpcumfuelcost[f,p-1])/(bpfueluse[f,p]-bpfueluse[f,p-1]);
```

```
var exper {k in TECH,TIME}; # <= max_exper[k];      # GW
var invest {TECH,REGION,TIME} >= 0;            # GW
var capacity {TECH,REGION,TIME};               # GW
var electricity {TECH,REGION,TIME} >= 0;     # TWh
var fuel_use {FUEL,REGION,TIME};               # TWh
var resources_used {FUEL,REGION,TIME};              # reserve units
var co2_emissions {TIME};                    # Gton CO2
var cum_fuelcost {FUEL,REGION,TIME};         # M$
var cum_invcost {TECH,TIME} <= max_cuminvcost;      # M$
var cost {TIME};                   # G$
var lambda {k in TECH, TIME, p in 1..npieces[k]} >= 0, <= bpexper[k,p];
                                    # breakpoint weight
var delta {k in TECH, TIME, 1..npieces[k]} binary;# segment indicator



# First some basic (bottom-up) energy system model relations:

subject to Fix_start {k in TECH, r in REGION}:
  invest[k,r,time0] = 0;


subject to Capacity {k in TECH, r in REGION, t in TIME}:
  capacity[k,r,t] = resid_capac[k,r,t] +
      sum {T in TIME: max(t-lifetime[k]+years, time0) <= T <= t} invest[k,r,T];


subject to Growth {k in TECH, r in REGION, t in TIME}:
  capacity[k,r,t] <= (1+market_growth)^years *
     if ord(t) > 1 then capacity[k,r,t-years] else start_capac[k,r];


subject to Electricity {k in TECH, r in REGION, t in TIME}:
  electricity[k,r,t] <= capacity[k,r,t] * availability[k,r] * 8760/1000;


subject to Energy_balance {r in REGION, t in TIME}:
  sum {K in TECH} electricity[K,r,t] >= demand[r,t];


subject to Peak_capacity {r in REGION, t in TIME}:
   sum {K in TECH: intermittent[K] = 0} capacity[K,r,t] >= peak_demand[r,t];


subject to Potential {r in REGION, t in TIME,
                     k in TECH: potential[k,'north'] > 0}:
  electricity[k,r,t] <= potential[k,r];
```

```
# Intermittent technologies are limited individually and collectively.

subject to Individual_limit {r in REGION, t in TIME,
                               k in TECH: intermittent[k] > 0}:
  electricity[k,r,t] <= intermittent[k] * demand[r,t];

subject to Intermittent_limit {r in REGION, t in TIME}:
  sum {K in TECH: intermittent[K] > 0} electricity[K,r,t] <=
                               max_intermittent * demand[r,t];

subject to CO2_emissions {t in TIME}:
  co2_emissions[t] = 1/1000 * sum {F in FUEL, R in REGION}
                               fuel_use[F,R,t] * fuel_co2[F];

subject to CO2_limit:
  years * sum {T in TIME} co2_emissions[T] <= total_CO2_limit;

subject to Fuel_use {f in FUEL, r in REGION, t in TIME}:
  fuel_use[f,r,t] = sum {K in TECH: fuel_tech[f,K] > 0}
                   electricity[K,r,t] / efficiency[K];

subject to Resources_used {f in FUEL, r in REGION, t in TIME}:
  resources_used[f,r,t] = 1 / 1000 *
    if f = 'oil' or f = 'uran' then
     years / (sum {R in REGION} fuel_reserves[f,R]) *
          sum {R in REGION, T in TIME: T <= t}
                (fuel_use[f,R,T] + non_electric_use[f,R,T])
    else if f = 'gas' and (r = 'north' or r = 'west') then
     years / (fuel_reserves['gas','north']+fuel_reserves['gas','west']) *
          sum {R in REGION, T in TIME: (R='north' or R='west') and T <= t}
                (fuel_use['gas',R,T] + non_electric_use['gas',R,T])
    else
     years / fuel_reserves[f,r] *
          sum {T in TIME: T <= t}
                (fuel_use[f,r,T] + non_electric_use[f,r,T]);

# This is a piecewise linearization of the convex fuel supply cost curves.
# I.e., fuel costs increase as fuel supplies are used.

subject to Cum_fuelcost {f in FUEL, r in REGION, t in TIME}:
  cum_fuelcost[f,r,t] >= << {P in 1..nfuel-1} bpfueluse[f,P];
```

```
                  {P in 1..nfuel} bpfuelcost[f,P] * fuel_reserves[f,r] * 1000 >>
                                                  resources_used[f,r,t];


# Definition of experience.
# (1 Wp of PV-H2 consists of 1 Wp PV and 1/7 W fuel cells in addition to the
# 1 W of electrolysis included in the investment costs.)


subject to Exper {k in TECH, t in TIME}:
  exper[k,t] = start_exper[k] +
     sum {R in REGION, T in TIME: T <= t}
       (invest[k,R,T] + if k = 'pv' then invest['pvh2',R,T]
            else if k = 'fc' then 1/7*invest['pvh2',R,T]);


# The next five constraints define the piecewise linear experience curves.


subject to PL_exper {k in TECH, t in TIME}:
  exper[k,t] = sum {P in 1..npieces[k]} lambda[k,t,P];


subject to Cum_invcost {k in TECH, t in TIME}:
  cum_invcost[k,t] = sum {P in 1..npieces[k]} (
     (bpcuminvcost[k,P-1] - bpinvcost[k,P]*bpexper[k,P-1])/1000 * delta[k,t,P] +
          bpinvcost[k,P]/1000*lambda[k,t,P]        );


subject to Lambda_delta_1 {k in TECH, t in TIME, p in 1..npieces[k]}:
  lambda[k,t,p] <= bpexper[k,p] * delta[k,t,p];


subject to Lambda_delta_2 {k in TECH, t in TIME, p in 1..npieces[k]}:
  lambda[k,t,p] >= bpexper[k,p-1] * delta[k,t,p];


subject to Delta_sum {k in TECH, t in TIME}:
  sum {P in 1..npieces[k]} delta[k,t,P] = 1;


# The next two constraints are not necessary, but they can reduce solution times
# considerably. Including them does not change the solution in any way.


subject to Exper_grows_1 {k in TECH, t in TIME,
                p in 1..npieces[k], T in TIME: ord(T)=ord(t)+1}:
  sum {P in 1..p} delta[k,t,P] >= sum {P in 1..p} delta[k,T,P];


subject to Exper_grows_2 {k in TECH, t in TIME,
                p in 1..npieces[k], T in TIME: ord(T)=ord(t)+1}:
```

```
    sum {P in p..npieces[k]} delta[k,t,P] <= sum {P in p..npieces[k]} delta[k,T,P];


# Finally the total system costs. Notice that late investments are salvaged.


subject to Cost {t in TIME}:
   cost[t] =
     1e-3 * discount * sum {R in REGION} (
         sum {K in TECH} (
           fixed_cost[K] * capacity[K,R,t] +
           var_cost[K] * electricity[K,R,t] ) +
         sum {F in FUEL: F != 'ren'} 1 / years *
           if ord(t)=1 then cum_fuelcost[F,R,t] else
           cum_fuelcost[F,R,t] - cum_fuelcost[F,R,prev(t)]   ) +
     sum {K in TECH} (1-salvage[K,t]) *
           if ord(t) = 1 then cum_invcost[K,t] else
           cum_invcost[K,t] - cum_invcost[K,prev(t)];


minimize total_cost:
  sum {T in TIME} cost[T] / (1+dr)^(T-time0);
```

genie.dat

```
set TIME := 1995 2005 2015 2025 2035 2045 2055 2065;


set TECH := convcoal convoil convgas gasturb hydro nuclear advcoal ccgt wind pv fc pvh2;
set FUEL := coal oil gas uran ren;
set REGION := north west south east;


param years := 10;        # years per period
param eps := 1e-8;        # small number
param dr := 0.05;         # discount rate


param market_growth := 0.3;    # maximum yearly market growth
param max_intermittent := 0.3; # maximum intermittent energy contribution
param total_CO2_limit := 292.5;      # 1995 emissions = 5.85 (5.85*60 = 351)
param max_cuminvcost := 40000; # upper limit for cum_invcost variable (for scaling)


param fuel_tech default 0 :=
     coal convcoal 1          coal advcoal 1
     oil convoil 1            oil gasturb 1
     gas convgas 1            gas ccgt 1   gas fc 1
     uran nuclear 1
     ren hydro 1          ren pv 1     ren wind 1   ren pvh2 1  ;


#fuelcell:       4500 = 3000 * 1.5 (for replacement of short-lived stack)
#pvh2:           15.1 = 8 + 5 (pv) + 15/7 (fc)
#                     $/kW      $/kW/year  $/MWh
param:   lifetime base_invcost  fixed_cost var_cost efficiency   :=
```

param:	lifetime	base_invcost	fixed_cost	var_cost	efficiency
convcoal	30	1300	30	4	0.38
convoil	30	800	15	1	0.36
convgas	30	750	15	1	0.36
gasturb	30	400	10	1	0.32
hydro	50	2500	30	0	1
nuclear	30	2500	50	2	1
advcoal	30	1400	30	5	0.45
ccgt	30	800	20	3	0.50
wind	30	1200	24	0	1
pv	30	7000	5	0	1
fc	30	4500	15	2	0.60

```
pvh2              30    550         15.1  2    1      ;


# high_exper 2045: nuclear 4 advcoal 4 ccgt 4 wind 3.5 pv 6 fc 4.5 pvh2 3
# high_exper 2065: double
param:    progress_ratio  npieces  high_exper  max_exper  intermittent  :=
convcoal       1.00          1       5000       30000        0
convoil        1.00          1       5000       30000        0
convgas        1.00          1       5000       30000        0
gasturb        1.00          1       8000       30000        0
hydro          1.00          1       5000       30000        0
nuclear        1.00          1       6000       30000        0
advcoal        0.95          6       4000       30000        0
ccgt           0.88          6       4000       30000        0
wind           0.88          6       5000       30000        0.2
pv             0.82         10      40000       70000        0.2   #15000 20000
fc             0.85          6       5000       30000        0
pvh2           0.85          8      30000       50000        0;    #7000 12000


# Starting capacity modified somewhat (calibrated to generation in 1995)
#
#                GW
param start_capac:
              north  west   south  east   :=
convcoal       35    339     33    130
convoil        35    272     92     83
convgas        32     82     45     13
gasturb        35    271     92     83
hydro         117    128    104     54
nuclear        43    269      5     17
advcoal         5    120      5     10
ccgt           30     70     15     35
wind           .7     3.6    .1     .6
pv             .01    .27    .01    .01
fc             .05    .19    .01    .05
pvh2           .8     2      .4     .8     ;


#              TWh        1995-2020       2020-2050    2050-
param:    demand_start demand_growth1   demand_growth2  demand_growth3  :=
    north     1592        .023            .012             .012
    west      6619        .019            .012             .012
    south     1453        .028            .024             .012
```

```
       east            1709           .052           .024            .012;


param savings := 0;              # annual demand-side efficiency improvements
param dist_efficiency := .903; # world consumption/generation 1995
param peak_multiplier := 1.5;  # (reserve capacity included)


#avail(pvh2) = avail(pv) * 0.9 * 0.7 (efficiencies for electrolysis & fuel cell)
param other_availability:
                 north west  south east   :=
convcoal         .75   .75   .75   .75
convoil          .8    .8    .8    .8
convgas          .8    .8    .8    .8
gasturb          .8    .8    .8    .8
hydro            .7    .7    .7    .7
nuclear          .75   .75   .75   .75
advcoal          .8    .8    .8    .8
ccgt             .8    .8    .8    .8
wind             .3    .3    .3    .3
pv               .125  .181  .220  .180   #load curve weighted pv_avail
fc               .8    .8    .8    .8
pvh2             .079  .114  .139  .113  ;
#pv              .14   .18   .22   .18    ; #average pv_avail;


param nfuel := 10;
#
# prices in $/MWh
#
# p1 = start price      p2 = price when reserves exhausted (linear increase)
#
#    100%: 7.5 16.1 12.5 11.4 50%:  6.0 12.6 9.65 9.55
#
#    max_fueluse 2,3,3,1
#
param:      p1    p2        max_fueluse       :=
coal        4.5   12.1          2
oil         9.1   14.7          4
gas         6.8   10.1          6
uran        7.8   11.0          1
ren         0     0             23      ;


# All of FSU in north, uranium guessed for Canada/USA, East low. (PWh)
```

```
param fuel_reserves:
          north  west   south  east   :=     #      sum
coal      1182   2352   491    1185          #      5210
oil       353    54     1283   82            #      1772
gas       603    111    607    83            #      1404
uran      266    210    178    4             #       658
ren       2323   2323   2323   2323   ;


# (TWh)
#
param non_electric_start:
          north  west   south  east   :=
coal      1160   2810   1330   7130
oil       3250   21120  7130   6000
gas       3490   9250   2730   830
uran      0      0      0      0
ren       0      0      0      0      ;


# Annual average growth rates to 2020
param non_electric_growth1:
          north  west   south  east   :=
coal      .001   .001   .02    .02
oil       .009   .009   .03    .03
gas       .016   .016   .031   .031
uran      0      0      0      0
ren       0      0      0      0      ;


# Annual average growth rates, 2020-2050
param non_electric_growth2:
          north  west   south  east   :=
coal      0      0      .01    .01
oil       0      0      .01    .01
gas       .01    .01    .02    .02
uran      0      0      0      0
ren       0      0      0      0      ;


param non_electric_growth3 := 0;


# ton/MWh (93,78,55 g/MJbr)
param fuel_co2 :=
    coal   .3348
```

```
    oil    .2808
    gas    .1980
    uran   0
    ren    0        ;


# TWh/year
param potential:
                north  west   south  east   :=
convcoal        0      0      0      0
convoil         0      0      0      0
convgas         0      0      0      0
gasturb         0      0      0      0
hydro           1520   1120   4490   1170
nuclear         0      0      0      0
advcoal         0      0      0      0
ccgt            0      0      0      0
wind            7680   7680   3040   820
pv              0      0      0      0
fc              0      0      0      0
pvh2            0      0      0      0     ;
```