Working Paper

Endogenized Technological Learning in an Energy Systems Model

Sabine Messner

WP-95-114
November 1995

IIASA
International Institute for Applied Systems Analysis □ A-2361 Laxenburg □ Austria
Telephone: +43 2236 807 □ Fax: +43 2236 71313 □ E-Mail: info@iiasa.ac.at

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1 Introduction

Energy modeling has, over the last decades, developed into an important tool for energy policy analysis. Beginning in the early seventies, when the so-called first oil price shock brought energy to the focus of attention, development of energy models was initiated with two major goals:

- find ways of reducing the dependence on costly imported oil, and
- evaluate the effect on the economy of various energy policies.

Two classes of models have emerged from this background: technology-oriented optimization and simulation models (now generally labeled bottom-up models) serving the first goal and economy-oriented models with emphasis on energy as a subsector of the overall economy (the top-down models in the present literature). A well-known early representative in the class of optimization models was BESOM, the Brookhaven Energy Systems Optimization Model [1]. Based on this model, MARKAL [2], an energy systems model with applications in many countries, has been developed. MARKAL is used by the International Energy Agency in the connex of the Energy Technology Systems Analysis Programme (ETSAP [3]) for energy technology-related analyses on the country level. Other representatives of the class of energy systems models are EFOM [4], the model employed by the European Union, and MESSAGE [5], the energy optimization model developed at IIASA on the basis of the Häfele-Manne [6] model.

For the second type of analysis, macro-economic models like general equilibrium models or neoclassical growth models were constructed to specially account for energy as a factor input or sector of the economy. In the US, such models were soon used for concerted analyses in the framework of the Energy Modeling Forum (EMF [7]). A famous proponent of the second model type and participant in the EMF is ETA-MACRO [8][1].

*Environmentally Compatible Energy Strategies Project at the International Institute for Applied Systems Analysis, A-2361 Laxenburg, Austria; e-mail:messner@iiasa.ac.at

[1]An analysis of the models currently involved in the EMF can be found in [9].

Further investigations went in the direction of linking bottom-up, technology-oriented models with top-down models depicting the overall economy. Early examples are the link of the Hudson-Jorgenson Model, which is a very disaggregated econometric model of the US economy with BESOM [10] and a model developed for Austria linking an economy model based on dynamic input-output tables with vintage capital structure and the energy systems model MESSAGE [11]. Presently most applications of such a hard-linking procedure of the two model categories are based on MARKAL/MACRO, linking the energy systems model MARKAL and the economy module of ETA-MACRO [12]. Wilson and Swisher [13] give a short introduction and critique of the top-down and bottom-up model types and the process of linking them, while Wene [14] evaluates different approaches for the linking procedure.

In the late eighties the application of energy-related models moved towards a new topic: global warming. Since the majority of man-made emissions of greenhouse gases is related to the use of energy[2], energy-related models are useful to analyze the problem and evaluate mitigation strategies. However, the long residence time of CO_2 in the atmosphere of 50 to 150 years [16] and the slow dynamics encountered in the historic structural changes of the energy system on a global scale, that suggests at least five decades for the penetration of new energy carriers [17], call for prolonged time horizons of model analyses, while conventional, energy policy oriented model analysis focussed on time frames of 20 to 50 years, depending on the scope of the analysis[3].

Prolonging the time horizon up to 2100, as done in most energy-related analyses of global change issues, brings new problems in model formulation and application that have to be addressed. One of these issues relates to the availability of depletable resources, where estimates are based on current technology and knowledge. However, by 2100 certainly more oil and gas fields will be discovered and new technologies will be available to increase the share of oil and gas recoverable from the known reserves. The historical record of the reserve to production ratio of oil, which holds an average of 30 years since 1900 [21] while at the same time production increased tremendously, supports this view. Another prominent example is the increase in reserves as published by USGS between the years 1987 [22] and 1991 [23]. Over this period, estimates of ultimate world resources of crude oil increased by 25% from 1744 to 2171 billion barrels. The majority of this increase was due to a reevaluation of middle east occurrences, which were 250 billion barrels or more than one third higher in the 1991 evaluation compared to 1987.

A second issue is technological performance. For a time frame of 30 years it is possible to view technological change as incremental and improvement rates as exogenously given (e.g., using the AEEI, an autonomous reduction in energy intensity over time, as in some models of the Energy Modeling Forum [24]). In the bottom-up energy-related analyses performed at IIASA beginning in the early eighties, technology was viewed as dynamic:

[2] According to IPCC [15] 77% of the CO_2 emissions in the eighties were related to the use of energy and cement production, while CO_2 is responsible for 60% of the man-made greenhouse effect [16].

[3] Most national energy plans based on model analysis had a time frame of 20 to 30 years (see [18] as an example), while major global analyses had an extended time horizon. An example of a comprehensive analysis from the early eighties that also included model analyses can be found in [19], a recent study of this type is described in [20].

characteristics of technologies were seen as dynamic over time, performance improves at certain, predefined rates.[4]

However, with time horizons approaching a century or more, this model externalization raises problems. Externally defined technology performance does not reflect actual model outcomes. The performance of a system will improve over time, independent if the system is employed or not. Finally, exogenizing technology in energy models implies that when the learning process is finished and the system has turned into a mature technology, it can be employed without previous investment in the learning process.

This paper presents an approach to internalize the process of technological learning in technology-related energy models by introducing technology cost as a function of cumulative acquired knowledge. This learning process reflects "learning by doing" (see Arrow [28] and Rosenberg [29]): The parameters of a technology improve as function of accumulated knowledge or cumulative output (or installed capacities). "Learning by doing" and the resulting learning or experience curves are among the best empirically corroborated phenomena in industry (Argote and Epple [30]).

2 Background

In the context of IIASA's work on global change, a set of models has been developed for the scenario-based analysis of energy strategies. This model set includes, among others, a framework to generate energy scenarios (the scenario generator [31]) and two energy models: a top-down energy-economy model, 11R[5], and a bottom-up model, MESSAGE III [5]. In the overall modeling process, MESSAGE and 11R are linked using a so-called softlinking process, where human interfaces, based on a formal decision framework, guide the process of scenario development for the three models, and finally decide on convergence criteria[6]. Figure 1 puts these models and the linking procedure into the overall perspective of integrated assessment modeling at IIASA.

MESSAGE III, the bottom-up energy systems model, is a dynamic linear programming model of the energy system on the technology level. Depending on the degree of disaggregation, different processes or technologies for producing a commodity can be evaluated. The integrated analysis of the overall energy system performed at IIASA includes the introduction of new energy carriers, like methanol or hydrogen. For this purpose, MESSAGE requires the description of the technologies involved, like hydrogen production with various competing technologies, and utilization of hydrogen for different end-uses, like aviation or industrial processes. Technology descriptions consist of the technical parameters (efficiency, plant life), the economic parameters (investment, O+M costs), and environmental effects related to the use of the technology (e.g., SO_2 or CO_2 emissions).

[4]Early model applications using this approach are described in [25], [26] and [27].

[5]11R is based on Global 2100, the model developed by Manne and Richels for long-term energy-economy analyses [32].

[6]This process has been evaluated and also compared to other ways of model linkage by Wene [14].

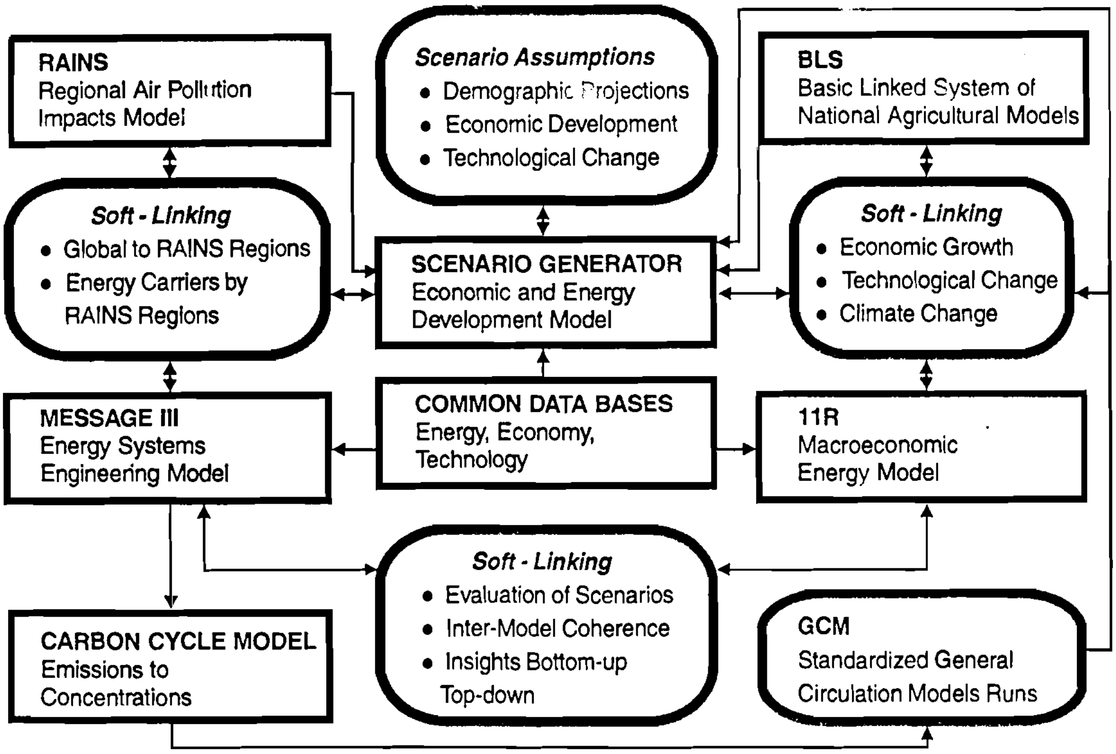

Figure 1: Integrated assessment at IIASA: models and linkages

Additional information concerns resource quantities, end-use demands (from the scenario generator) and technical, economic and socio-political constraints. Such additional constraints include maximum utilization rates for renewable sources of energy, constraints on the market penetration of new technologies, or policy-oriented limits, like limiting the share of nuclear energy accepted in the electricity generation system. Generally, most parameters used in MESSAGE are scenario-dependent.

For the most recent application of MESSAGE, the long-term energy scenarios presented at the 16^{th} congress of the World Energy Council in Tokyo in October 1995, three families of scenarios were developed. For each of these families or Cases all generic descriptors of the energy system, like GDP, resource availability, technological change, availability and acceptability of renewable sources of energy, and public attitude towards the environment are varied in a consistent manner. The Cases are characterized as follows:

- CASE A: High Growth
  The future economy and energy system is characterized by high rates of economic growth and fast technological progress.
- CASE B: Middle Course
  A "pragmatic" scenario with moderate growth expectations and lower technological dynamics.
- CASE C: Ecologically Driven
  The most challenging case with optimistic assumptions about economy and technology and, compared to CASE A, strong emphasis on environmental issues and international equity.

The scenarios are fully described in [20], while [33] gives a short overview of the study.

In terms of describing the scenarios with the energy systems model MESSAGE, assumptions concerning technological change had to be concerted with the scenario definition. Figure 2 displays the kind of model employed: over time, assumedly with increasing knowledge and cumulative application and construction of the technology, costs are reduced and performance parameters, like the conversion efficiency, improve (Source: [20]). The technology data bank of MESSAGE includes time series with improving performance and decreasing costs for all important technologies, especially new systems like PV electricity generation or all technologies related to hydrogen production and use. The rates of change vary over the three cases, in line with the assumptions concerning economic growth and technology dynamics.

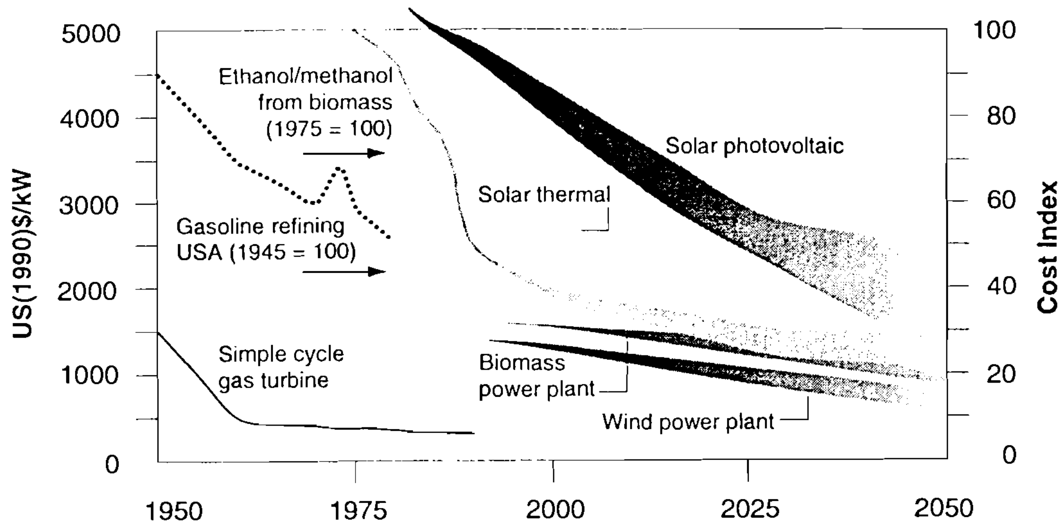

Figure 2: Examples of historical and assumed future technology cost improvements

The modeling process described has a severe shortcoming: the model can decide (and actually decides also) to use a technology later in time, i.e., when the costs are already improved, it thus can avoid investments in the learning phase of the technology. Technology improvements and learning in this case come as a "free good". The result will be rather late adoption of new technologies, deciding for their use only at the time when the technology parameters already characterize a mature, cheap technology with high market share and acceptance. In energy optimization models, a common way to combat these problems is by limiting growth rates over time, simulating a market penetration process.

The technology dynamics should however be conceived differently. Diffusion proceeds gradual (and not instantaneous on a large scale) by progressively exploiting niche markets. These together with continued R&D provide for "learning by doing" (in the manufacturing of technologies, equipment, etc.) and "learning by using" by accumulation of experience of using technologies (in turn an important source of information flow for the improvements in design characteristics and economics of new technologies). Thus learning is contingent on actual implementations and experimentation with new technologies, and the more implementation and experimentation takes place, the higher the resulting learning and improvements of technologies. Thus, future technology improvements become endogenized, i.e. a function of a particular development (investment) strategy chosen. A frequently used representation of this learning process is to express the learning (e.g. cost reductions) as a function of cumulative installations (sales, or installed capacities on new equipment). Figure 3 displayes similar information as Figure 2, but with cumulative investment (or knowledge) on the horizontal axis.

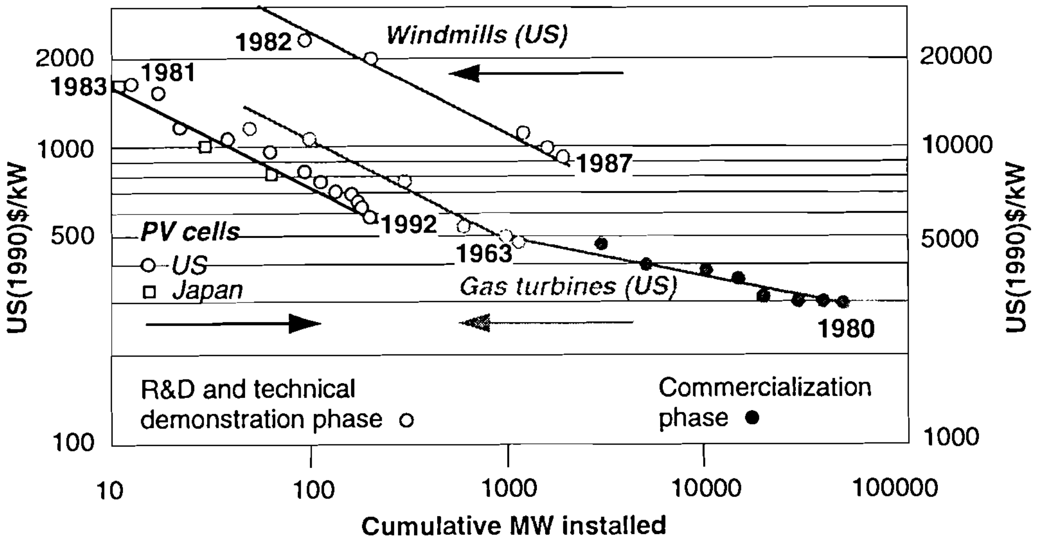

Figure 3: Technology learning: improvement in the costs of per unit of output versus cumulative output.

Generally, linear programming models like MESSAGE cannot represent such relations, because they are non-convex. The most important feature of non-convexity is, that feasible solutions to a problem exist with no direct connection from one of these solutions to the other. For the model of technological learning this implies, that in the linear model the mature technology parameters are available without investing in the learning process, i.e. there is a direct connection from zero installations to the parameters of the mature technology.

For linear programming models, the standard methodology to cope with non-convex relationships is mixed integer programming (MIP). Non-convex relations are, like all nonlinearities, described by step-wise linearization. Additionally, integer variables are used to enforce the sequence in the curve, in our case the relation between total size of the market and technology cost. Cheap technologies are only possible when the market is large, for smaller markets (or cumulative installations) higher prices have to be paid. A pure linear programming model could use the cheap technologies irrespective of the actual market size.

3 Modeling technological learning

For first experiments with the endogenized process of technological learning, investment costs were chosen as dependent variable. Process models like MESSAGE require technology costs as specific values, e.g. per kW. In the model formulation these costs are multiplied with the annual new installations and consequently yield the overall cost. By using dynamic (time-variable) investment costs, technological learning is reflected in a static way. The resulting investment strategies do not influence specific investments. Investment costs of one technology are then commonly expressed as

$$\sum_{t=1}^{T} d_t \Delta_t Y_t \times i_t$$

in the objective function where
d_t discount factor for period t
Y_t annual investment in period t
Δ_t number of years in period t
i_t specific investment cost in period t
T number of periods in the model.

Endogenizing technological learning in a technology-oriented model requires representing the process of change in technology parameters during the learning process. The measure used for cumulative knowledge acquired in the learning process is cumulative installed capacity. Dynamized specific investment costs as part of the objective can be expressed as

$$\sum_{t=1}^{T} d_t \Delta_t Y_t \times i_t(C_t)$$

with

$$C_t = \sum_{\tau=1}^{t} \Delta_\tau Y_\tau$$

where the specific investment cost i_t is a function of cumulative investment C_t.

In terms of a mixed integer formulation this relationship is best expressed using Special Ordered Sets (SOS sets) of type 2. They are characterized by the following:

- a SOS-2 set consists of at least two variables, and
- only two adjacent variables in one set can take non-zero values.

For a more comprehensive explanation, see e.g. [34]. By their characterization SOS-sets are very well suited to interpolate non-convex relationships. The corresponding formulation of the cost curve of technological learning using a SOS-2 formulation is:

1. Interpolate cumulative investments, i.e. determine in which part of the learning curve the technology is:
$$\sum_{n=1}^{N} c_n S_{nt} = \sum_{\tau=1}^{t} \Delta_\tau Y_\tau$$
2. Determine the investments to be paid in the period, cumulating all investments over time and using the specific investment costs in accordance with the cost curve:
$$\sum_{\tau=1}^{t} I_\tau = \sum_{n=1}^{N} i_n S_{nt}$$
3. Force the sum of the SOS-variables to be equal to one for correct interpolation:
$$\sum_{n-1}^{N} S_{nt} = 1$$
4. The objective function includes the investment variables, discounted as usually applied in MESSAGE with a discount rate of 5% per year:
$$\sum_{t=1}^{T} d_t I_t$$

where the following variables and parameters are used:
S_{nt} are variables of the SOS-2 set for period t
I_τ are the additional investments in the technology in period t
c_n represents the interpolation points for capacity
i_n represents the interpolation points for average costs

This formulation is added to the standard formulation of MESSAGE, as it is described in [5], and solved with a commercial MIP package, CPLEX [35].

4 Application and Results

The three families of scenarios as described in section 2 have, among others, different descriptions of technology dynamics over time. Cases A and C have dynamic expectations of potential technology improvements, while Case B presents a more conventional view of the future, i.e. more static investment costs. Table 1 presents the specific investment costs for new electricity generation technologies which could provide a significant share of electricity by the year 2050. It includes the costs for 1990, i.e. estimates of present costs for new installations, and the cost in 2050 for Cases A and B. These cost estimates were based on the data collected in CO2DB, the IIASA CO_2 mitigation technologies inventory [36]. A statistical analysis of these underlying data is performed in [37].

Table 1 shows that in the Middle Course Case (B) the potential for improvements for advanced coal and new nuclear technologies was assumed to be in the range of 10%, gas combined cycles improve by nearly 20%, while the cost reduction potentials for the

Table 1: Investment costs of selected technologies, US$(90)/kW

Technology	1990	2050	
		Case B	Case A
CoalAdv	1650	1500	1350
GasCC	730	600	400
NewNuclear	2600	2300	1800
Wind	1400	900	600
SolarTH	2900	1600	1200
SolarPV	5100	2000	1000

renewable technologies are highest with 35% for wind, 45% for solar thermal and 60% for PV electricity generation. In case of more dynamic technological change, the potentials for improvements lie between 18% for advanced coal-based electricity generation and 80% for solar PV. The cost ranking of the technologies is changed by these cost reductions. In Case A even the ranking among the solar technologies is reversed: expectations are for PV cells to become more economical than solar thermal electricity generation.

The three Cases were modeled on the basis of eleven world regions. For each of these regions energy conversion is modeled from primary energy extraction and imports up to final utilization in the end-use sectors. The regional energy models are interlinked by global energy trade, the whole system is solved simultaneously. This world energy model has in the order of 35000 variables and 50000 constraints, depending on the Case, that determines the number of new technologies available in the system.

For additional investigations and development of new methodological approaches a small version of the world model was developed. This small version, which consists of only one region depicting the world as a whole, and which presently does not include end-use technologies, but rather includes demands for types of final energy carriers (gaseous, liquid, solid, electricity and district heat) is used for first experiments with the approach to internalize technological learning in MESSAGE III. Model size is approximately one tenth of the full model with 2700 columns and 3400 rows.

Technological learning in terms of reduction of investment costs as a function of cumulative installations is included into this model for the technologies listed in Table 1. The learning process starts at present costs and can, by accumulating experience, reach the level assumed for Case A. This means that for solar PV a reduction by a factor of 5 can be reached, while the reduction potential for gas combined cycles is approximately 45%, from 730 US$/kW to 400 US$/kW.

The comparative analysis is based on a "static" case, where the investment costs of the new technologies are assumed to remain at the 1990 level over the whole time horizon. Figure 4 shows the energy mix used for electricity generation in the static case for the years 1990, 2020 and 2050. In this case the mix of electricity generation, which includes 38% coal, 14% gas, 17% nuclear and 30% other sources (predominantly hydro-power) in

1990, encounters a major shift towards nuclear energy. By 2050, 55% of all electricity is generated from nuclear energy. The second-largest share of 33% is accomplished by coal-based systems, with standard coal-fired power plants increasing their production from presently 515 GWyr to 911 GWyr and advanced coal-based systems supplying additional 641 GWyr by 2050. Gas-based electricity generation in steam turbines (184 GWyr in 1990) is virtually phased out by 2050, while gas-fired combined cycles provide 444 GWyr or 10% of all electricity (a lower share than in 1990). Wind generators start to be employed at a larger scale only after 2030, when fossil energy sources become more expensive (the shadow price of oil reaches 38$/boe in 2030). Solar thermal systems are first used in 2050, but their contribution is below 1%. PV's do not become competitive at the energy prices prevailing in this scenario.

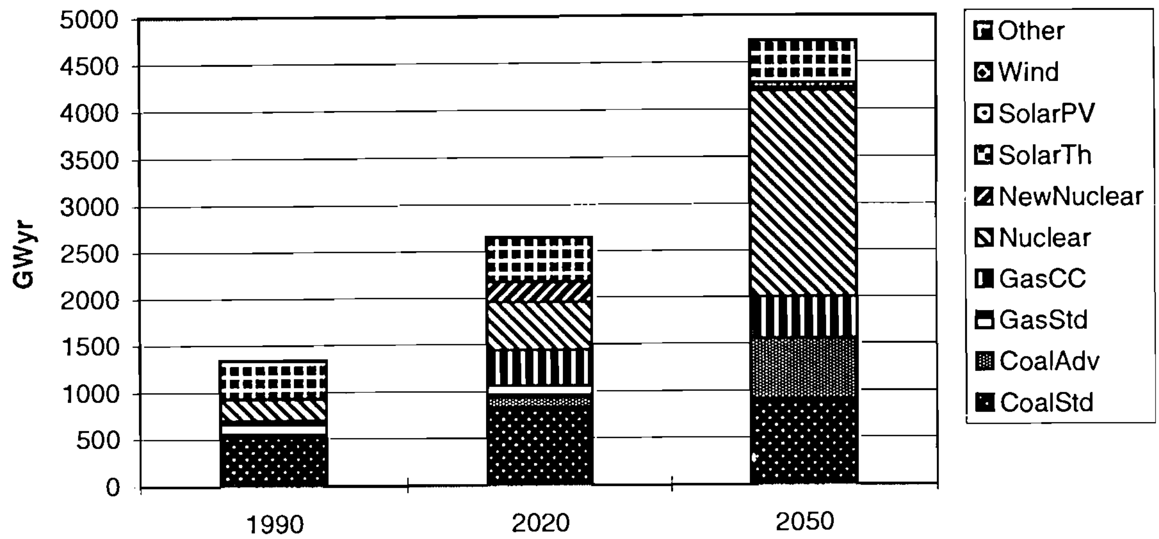

Figure 4: Electricity generation in the static case, 1990, 2020 and 2050

The static case, as presented here, reflects the usual paradigm of running out of resources: marginal oil and gas resources are expensive, nuclear energy is required to provide energy at attractive prices, and coal, with its vast resource base at economic costs, is the second choice for electricity generation. New, renewable energy sources cannot provide electricity at competitive prices, and natural gas resources are not cheap enough to provide significant shares of electricity.

The introduction of technological learning as described in section 3 for the electricity generation technologies in Table 1 changes the picture dramatically (see Figure 5).

The use of standard technologies (coal and nuclear in addition to gas) is reduced considerably (by 2050, only 14% of electricity is generated from these two sources), while new technologies, which have potential for technological learning, expand considerably. Wind generators, solar electricity generation and new nuclear generators are employed, and also the use of advanced coal-based systems is increased a little. In 2020 two changes can be realized, namely the starting penetration of solar PV and wind systems, and the larger contribution of new nuclear reactors to the smaller overall share of nuclear energy. By 2050, the coal share is 17% versus 33% in the static case and nuclear supplies 36%

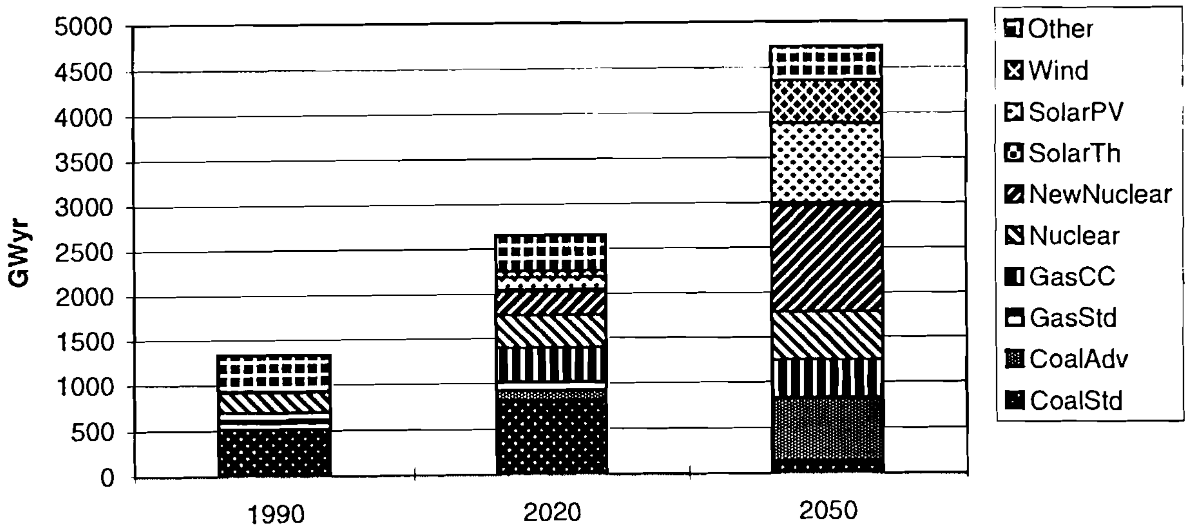

Figure 5: Electricity generation in the case with learning in electricity generation, 1990, 2020 and 2050

compared to 46%, while solar PV contribute 19% and wind energy amounts to 10% of electricity generation (compared to 0.7 and 1% in the static case, respectively). The effect of technological learning on marginal production cost (or shadow prices) provides stable prices of electricity compared with a 13% increase of marginal cost in the static case.

One notable result of this analysis is that gas-based combined cycle power plants are used to a lower degree compared to the static case. Although the costs of these systems have a reduction potential of 45%, other systems become more attractive. The main reason is the high share that fuel costs have in the production cost of gas-based electricity generation systems. Over the planning horizon, the shadow price of natural gas doubles from roughly 16$/boe in 1990 to 32$/boe in 2050 in both cases, making gas an unattractive source of electricity.

Since the growing price of natural gas due to depletion of cheap reserve categories shows a major effect on model results, a logical next step in model development is an extension of the principle of technological learning to the extraction technologies. The assumption in Case A concerning technological learning in oil and gas extraction (applied to the more expensive categories only) is that up to 2050 a reduction of 40% could be achieved. This assumption is incorporated into the small world model as potential cost reduction.

In this new case, marginal prices of primary energy are reduced considerably: in 2050, oil is priced at 35$/boe instead of about 40$/boe in the other two cases, while gas costs 23$/boe instead of 32$/boe. At the same time, cumulative use of oil over the 60 years is increased by 5% or 18 Gtoe, cumulative gas use is 10% or 30 Gtoe higher.

In the electricity generation pattern in 2020 (see Figure 6) there is no major difference to the previous case, but by 2050 the contribution of gas-based combined cycles reaches a higher share than in both other cases, 36% of electricity. This expansion is reached at the expense of nuclear (no standard nuclear systems are used and the advanced systems contribute 25% less) and ... coal, that contributes only 4% compared to 15% in the previous case.

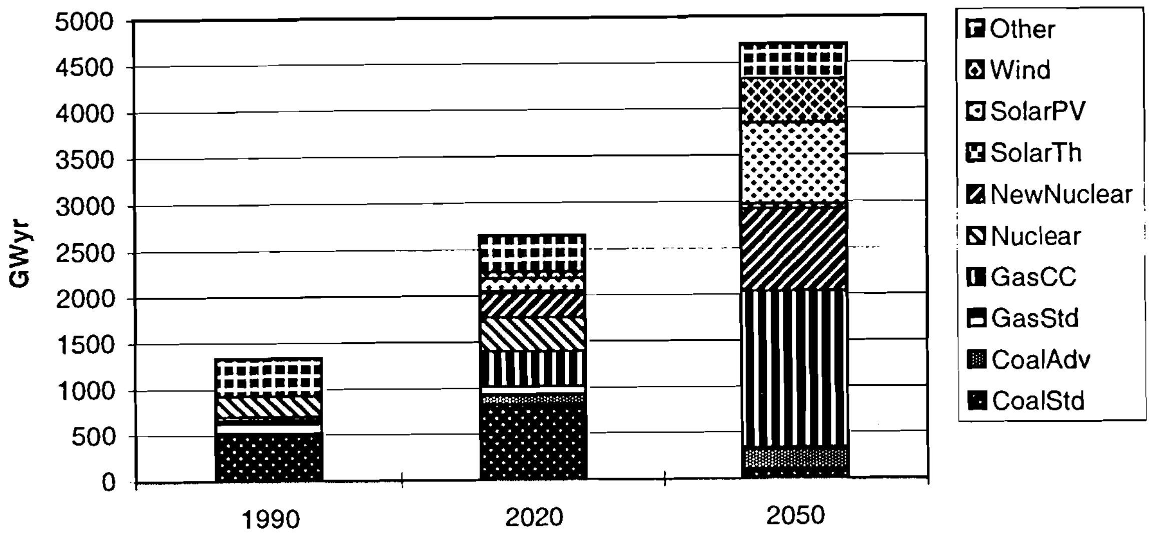

Figure 6: Electricity generation in the case with learning in electricity generation and extraction, 1990, 2020 and 2050

5 Comparison to Standard Applications

The analyses in section 4 have shown, that modeling technological learning in terms of cost reduction with growing experience dramatically influences model outcomes compared to static assumptions. In the following this approach is compared to using dynamic parameters, i.e. introducing a deterministic trajectory of future cost reductions into the model parameters.

The small world model was applied with the cost trajectories underlying Case A, reaching the level described in Table 1 by 2040. Figure 7 compares the electricity generation patterns in 2050 for this case (labeled dynamic) with the static case and the case with endogenized learning in electricity generation and extraction.

In the dynamic case, where the cost trajectories correspond to IIASA-WEC Case A, coal is reduced to approximately 5%, standard nuclear technologies are phased out and partly replaced by advanced nuclear systems. However, the major share of electricity generation in this case is supplied by gas-based combined cycle power generation. The overall contribution of solar systems is about 20%, and PV start to penetrate the market.

Comparing this dynamic case with the learning case shows some small and one major difference, which concerns solar electricity generation. Overall solar electricity generation is the same, but in the learning case nearly all comes from PV, while in the dynamic case some 60% are still from thermal systems. This is an effect of the cross-over of the costs curves of the two solar electric systems, which is at a fixed point in time in the dynamic

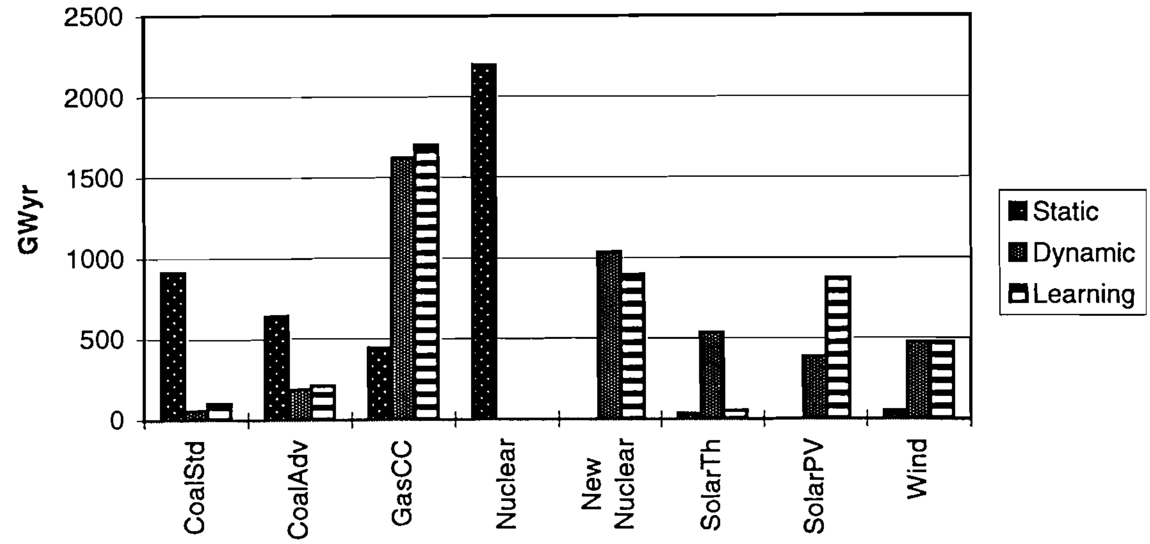

Figure 7: Electricity generation in 2050 by case and technology

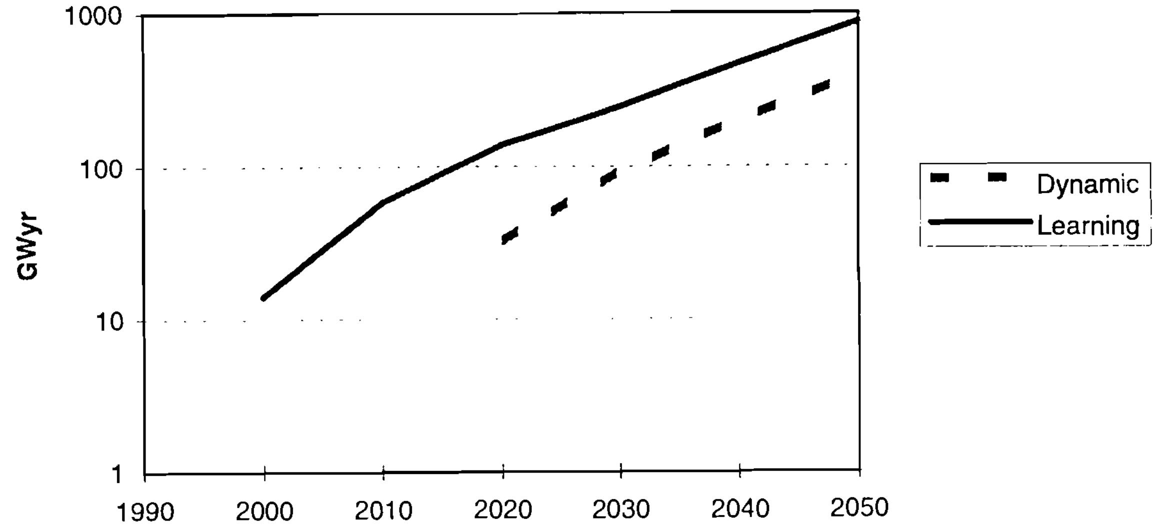

Figure 8: Electricity generation from solar PV in the dynamic and learning cases, 1990 to 2050

case, while it can be influenced by higher investments in PV systems in the learning case. Consequently, PV penetration starts already in 2000 with endogenized learning (as compared to 2020 in the dynamic case) and penetration rates are also much higher (see Figure 8).

The specific investments per kW installed for solar PV systems in the dynamic and learning cases are contrasted in Figure 9. The assumption in Case A is a linear cost decrease over 50 years at around 3% per year. In the learning case, the final level of US$ 1000/kW is reached 10 years earlier, in 2030, and the development of the costs over time is nonliner. The initial small reduction of 10% between 1990 and 2000 is followed by a major step of reducing the costs by more than 50% up to 2010. Thereafter, another large step of 40%

reduction between 2010 and 2020 follows. The final reduction up to 2030 again is in the range of 10%.

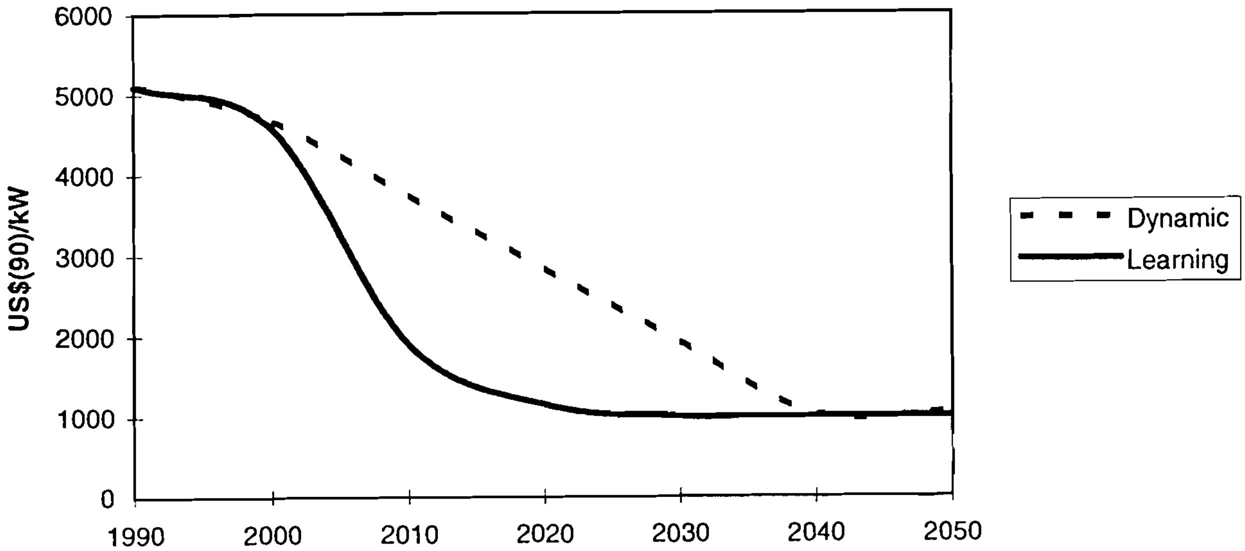

Figure 9: Specific investment cost for PV systems in US$(90)/kW in the dynamic and learning cases, 1990 to 2050

Similar comparisons can be made for all technologies. One interesting case is that of advanced coal shown in Figure 10. Initially, no investments takes place in this system, so costs are not reduced in the learning case up to 2000. Thereafter, learning starts slowly up to 2010, thereafter accelerates and by 2030 reaches the ultimate level of cost improvement. In the dynamic case, on the other hand, cost improvements are again predefined with a given pattern over time. Although investments in advanced coal systems start only in 2010, parameters improve in a static manner over time.

Figure 11 shows the effect of dynamizing investment cost (dynamic case) and endogenizing technological learning in terms of investments (learning case) by comparing the investment profile for these two cases to the investment profile of the static case. Investments in the energy sector today are at least 10% of international credit financing, which presently is around US$ 3.6 trillion (10^{12}) [38]. In the static case, the annual energy investments grow at an average annual rate of 2.4% and reach 4.2 times the level of 1990 by 2050. This trajectory is taken as basis for the comparison in Figure 11 and shown as 100% there. If specific investment costs of new technologies decline over time (dynamic case), the overall investments start higher than in the static case to initialize faster market penetration of the new technologies, which after 2020 reduces investments by up to 20%.

In the case with endogenized technological learning investments in expensive technologies like solar PV is started earlier, as was shown in the previous analysis. Consequently, overall investments are even higher than in the dynamic case. However, in the longer run the reduction in investment starts earlier and sustains a higher level in the case with endogenized learning compared to the dynamic case. Up to 2020, the dynamic case has 0.2% higher cumulative investments than the static case, while the case with endogenized technological learning invests 1.5% more in the energy sector. Between 2020

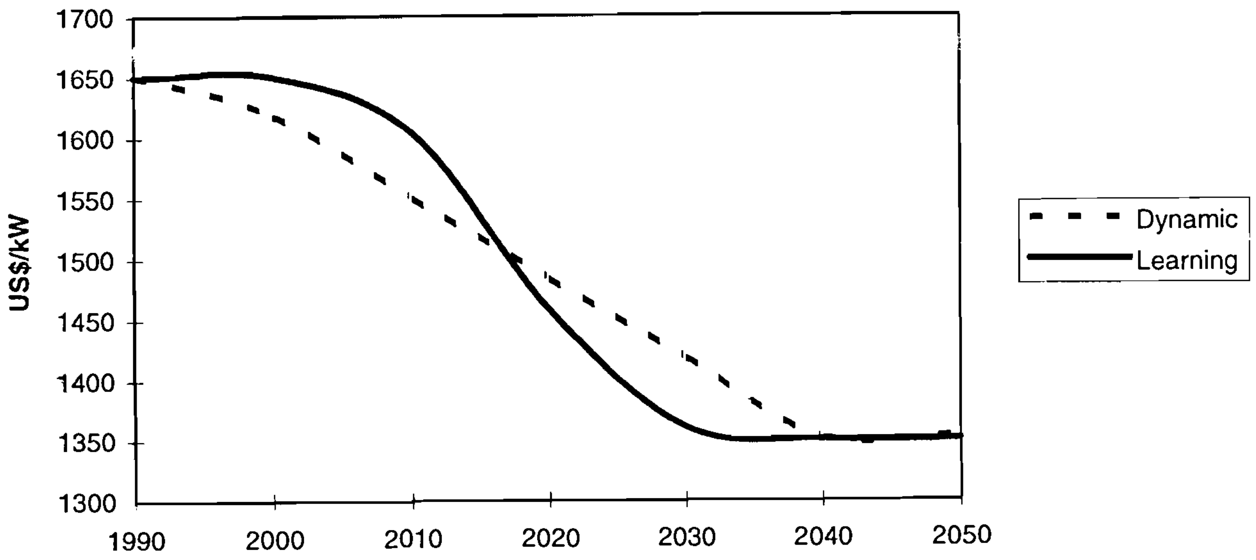

Figure 10: Specific investment cost for advanced coal power plants in US$(90)/kW in the dynamic and learning cases, 1990 to 2050

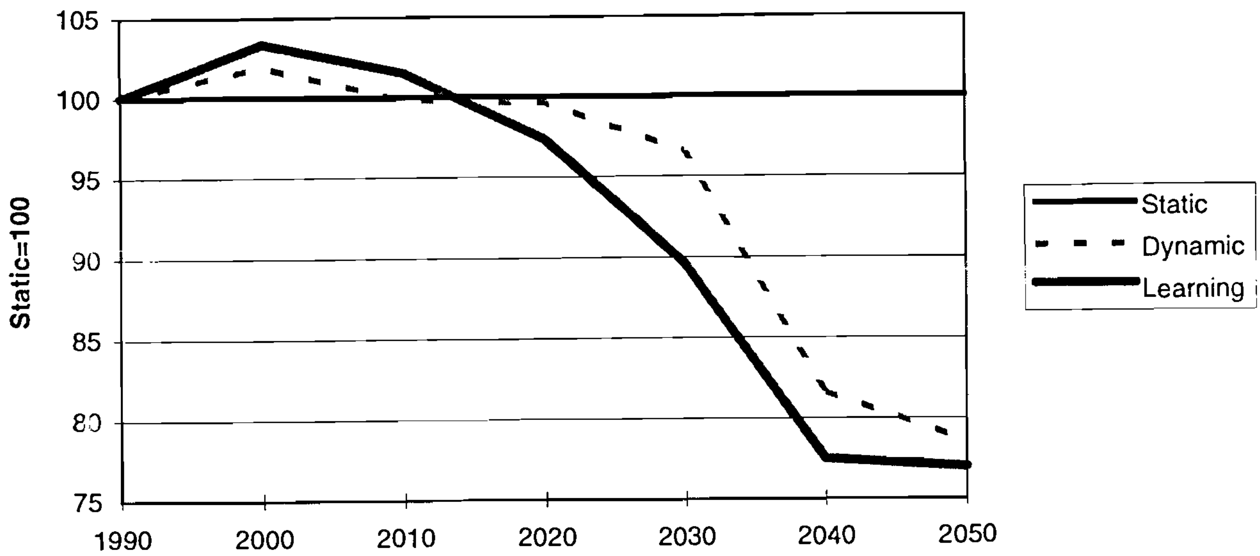

Figure 11: Annual investments in the dynamic and endogenized learning cases compared to the static case, 1990 to 2050.

and 2050, both cases show reductions in cumulative investments, that are 50% higher in the case with endogenized technological learning (-13.2% compared to the static case) than in the dynamic case (-8.7% compared to the static case). Over the whole time horizon from 1990 to 2050, cumulative investments in the dynamic case are 6.6% lower than in the static case, while this figure is 9.7% for the case with endogenized learning. Redistributing the investment decisions to enhance the process of technological learning, reduces overall capital investments in the energy sector by 50% more than just envisioning a time-dependent learning process, as it is modeled in the dynamic case.

The objective function of the optimization runs, which is the sum of all discounted costs (or the net present value) of the energy system (excluding energy utilization) over the whole horizon up to 2050, using a discount rate of 5%, is US$(90) 186.2 trillion ($10^{12}$) in the static case. In the dynamic case it is reduced by US$(90) 1.79 trillion, while the reduction is US$(90) 2.22 trillion or 24% more in the case with endogenized learning.

6 Conclusions

Technological learning has been endogenized in the energy systems model MESSAGE III in terms of cost reduction as a function of accumulated knowledge. Results of model runs for a comprehensive model of the global energy system show drastic changes in model results compared to using static model parameters. Opposed to the mere inclusion of time-dependent cost trajectories this representation yields different results in cases where faster cost reductions for attractive technologies can be achieved by higher initial investments. This has been shown for the case of PV electricity generation, where the reduction potential is considerable. In the complete absence of technological learning, these systems are not employed, while in the case of a trajectory for system cost, a share of 8% of electricity generation is reached by 2050. By endogenizing the process of knowledge accumulation and cost reduction in the model, this share is increased to nearly 20%[7].

An analysis of the investment requirements and objective function values reached in the three model runs, the static, dynamic and learning cases, shows the influence of endogenizing technological learning in the modeling approach: Cumulative investments are reduced considerably (by 13.% compared to the static and approximately 5% compared to the dynamic case). But endogenizing technological learning also reduces the overall discounted costs of the energy system by 1.2% compared to the static case, that is 0.2% more than the dynamic case. Compared to the static case the overall cost reduction is US(90)$ 2.2 trillion.

The message from this experiment is that early decisions for the introduction of new technologies are essential in reaching good economic performance over time. In real life, where "technological innovations would consist mostly of non-starters" [39], the winners and loosers are not known from the beginning. Therefore, diversification into various candidates and the acceptance to take a certain degree of risk will be required[8]. But finally the chance is much higher then that efficient and cheap technologies will be available for future energy supplies.

[7] The discount rate used for this analysis is 5%, as in the underlying IIASA and WEC study [20].

[8] This is also supported by an analysis including the uncertainties of future investment cost [40].

7 Outlook

The approach to internalize technological learning in the energy systems model MESSAGE for technology investment costs has proven to yield fruitful results with respect to the introduction rates and points in time for new technologies. Further research will broaden the scope of the analysis to include more technology parameters. Conversion efficiency, the most important technical parameter describing a technology, and operating costs as a proxy for "learning by using" are prime candidates here.

Learning processes of single technologies are also interrelated. Additional research is required on which technologies could be connected in terms of the learning process, and where a formalized model of these interrelations (technology clustering) should be included in the model. A historical example of such cross enhancements is oil and gas extraction: extraction of natural gas has certainly profited considerably from research and experience in the oil extraction technologies.

Another research effort to improve the representation of technological forecasting in the framework of MESSAGE III relates to the uncertainties with respect to model parameters. An application of a new and very efficient approach to include stochasticity for investments [40] also yields more technological diversification (hedgeing against risks of future high costs). A combination of the two approaches could provide interesting and valuable results: the process of technological learning including uncertainties concerning the achievable cost reductions could be analyzed.

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