ENDOGENIZED TECHNOLOGICAL LEARNING IN AN ENERGY SYSTEMS MODEL

Sabine Messner
International Institute for Applied Systems Analysis
Laxenburg, Austria

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International Institute for Applied Systems Analysis, Laxenburg, Austria
Tel: +43 2236 807 Fax: +43 2236 73148 E-mail: publications@iiasa.ac.at

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Endogenized technological learning in an energy systems model

Sabine Messner*

International Institute for Applied Systems Analysis, A-2361 Laxenburg, Austria
(e-mail: messner@iiasa.ac.at)

Abstract. Technology dynamics is endogenized into a bottom-up energy systems model. Mixed integer programming is used to incorporate into the model the non-convex relation between declining specific investment in energy technologies and overall experience or capacities installed. The initial results achieved with this approach show the importance of early investment in new technology developments. New technologies will not become cheaper irrespective of research, development, and demonstration (RD & D) decisions; they will do so only if determined RD&D policies and investment strategies enhance their development.

Key words: Technological learning – Energy modeling – Mixed integer programming

JEL-classification: C61; O14; O33

1 Introduction

Over the past decades, energy modeling has developed into an important tool for energy policy analysis. In the early 1970s, when the oil price shock made energy a major focus of attention, the development of energy models was initiated with two major goals:

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

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* Environmentally Compatible Energy Strategies Project at the International Institute for Applied Systems Analysis.

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 an emphasis on energy as a subsector of the overall economy (the top-down models in the present literature). A well-known early energy optimization model 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. The Energy Technology Systems Analysis Programme (ETSAP [3]) of the International Energy Agency uses MARKAL for energy technology-related analyses at the country level. Other representatives of this class of energy systems models are EFOM [4], the model employed by the European Union, and MESSAGE [5], the energy optimization model developed at the International Institute for Applied Systems Analysis (IIASA) on the basis of the Häfele-Manne [6] model.

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

Further investigations worked toward linking bottom-up, technology-oriented models with top-down models depicting the overall economy. Early examples include the linking of the Hudson-Jorgenson model, a very disaggregated econometric model of the US economy, with BESOM [10], and a model developed for Austria that joins a macro-model based on dynamic input-output tables with a vintage capital structure and the energy systems model MESSAGE [11]. Currently, many attempts at combining models from the two categories are based on MARKAL/MACRO, which links the energy systems model MARKAL with 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 1980s, the application of energy-related models moved toward a new topic, global warming. Because the majority of man-made emissions of greenhouse gases are related to the use of energy,[2] energy-related models are useful in analyzing the problem and evaluating mitigation strategies. Conventional, energy-policy-oriented model analysis focuses on time frames of 20–50 years, depending on the scope of the analysis.[3]

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

[2] According to the IPCC [15], 77% of overall CO_2 emissions in the 1980s were related to the use of energy and cement production. On the other hand, CO_2 is responsible for 60% of the man-made greenhouse effect [19].

[3] Most national energy plans based on model analysis had a time frame of 20–30 years (see [16] 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 [17]; a recent study of this type is described in [18].

However, the long residence time of carbon dioxide (CO_2) in the atmosphere (50–150 years [19]) and the slow dynamics encountered with structural changes of the energy system on a global scale (suggesting at least five decades for the penetration of new energy carriers [20]) call for prolonged time horizons for model analyses.

Prolonging the time horizon up to the year 2100, as is done in most energy-related analyses of global change issues, brings new problems in model formulation and application that must be addressed. One of these issues relates to the availability of depletable resources. Present estimates of these resources are based on current technology and knowledge. However, by 2100 more oil and gas fields will certainly be discovered, and new technologies will be available to increase the share of oil and gas recoverable from known reserves. The historical record of the reserve-to-production ratio of oil supports this view: Since 1900 the ratio has averaged 30 years [21] while at the same time production has increased tremendously. Another notable example is the increase in the size of the estimated reserves as published by US Geological Survey (USGS) between the years 1987 [22] and 1991 [23]. Over this period, estimates of the ultimate world resources of crude oil increased by 25%, from 1,744 to 2,171 billion barrels. The majority of this increase (250 billion barrels) was due to a reevaluation of Middle East occurrences which alone made the 1991 evaluation one-third higher than the 1987 evaluation.

A second issue is technological performance. For a time frame of 30 years it is possible to view technological change as being incremental and improvement rates as being 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 in the early 1980s, technology was viewed as dynamic and performance improved at certain, predefined rates.[4]

With time horizons approaching a century or more, however, this model externalization raises problems. Externally defined technology performance does not reflect actual model outcomes. In such simplified treatments, the performance of a system will improve over time regardless of whether or not the system is employed. Finally, exogenizing technology in energy models implies that, when the learning process is finished and the technology has matured, it can be employed without previous investment in the learning process.

This paper presents an approach to internalizing 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 [28] and [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 characterizing technological change in industry (Argote and Epple [30]).

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

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. Among the models included in this set are 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 through a so-called soft-linking process where human interfaces use a formal decision framework to guide the process of scenario development for the three models and finally decide on convergence criteria.[6] Figure 1 shows these models and the linking procedure as part of the overall framework of integrated assessment modeling at IIASA.

MESSAGE III, the bottom-up energy systems model, is a dynamic linear programming model of the energy system at the technology level. Depending on the degree of disaggregation, different processes or technologies for producing a commodity can be evaluated. IIASA's integrated analysis of the overall energy system includes the introduction of new energy carriers (for example, methanol or hydrogen). For this purpose, MESSAGE requires descriptions of the technologies involved, such as hydrogen production with various competing technologies and the

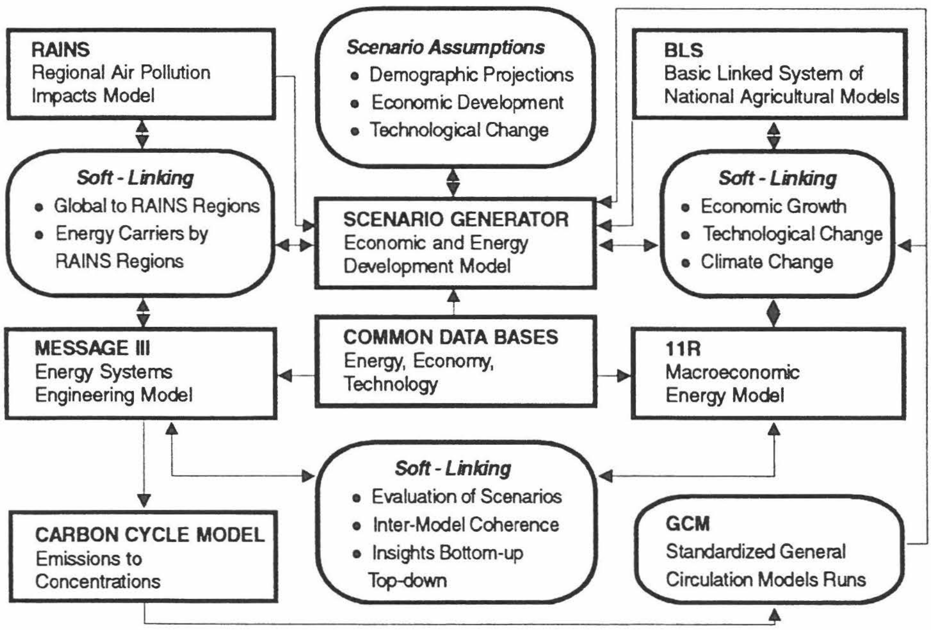

Fig. 1. Integrated assessment at IIASA: models and linkages

[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 compared with other methods of model linkage by Wene [14].

utilization of hydrogen for different end uses (such as aviation or industrial processes). Technology descriptions consist of the technical parameters (efficiency, plant life), the economic parameters (investment, operating and maintenance costs), and the environmental effects related to the use of the technology [e.g., sulfur dioxide (SO_2) or CO_2 emissions]. Additional information concerns resource quantities, end-use demands (from the Scenario Generator), and technical, economic, and sociopolitical 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, such as limiting the share of nuclear energy accepted in the electricity generation system. Generally, the parameters used in MESSAGE are scenario dependent.

The most recent application of MESSAGE was performed in collaboration with the World Energy Council (WEC). An integrated assessment framework was used to explore the prospects for improving the global availability and quality of energy services, as well as the wider implications these improvements may have. The study explores a broad range of global energy developments and their consequences, such as the likely financing needs and environmental impacts. This two-year IIASA-WEC study is presented in *Global Energy Perspectives to 2050 and Beyond* [18] and a number of related publications ([33], [34], [35]).

The IIASA-WEC study centers on three cases of future economic and energy development for 11 world regions, Cases A, B, and C. The cases are characterized as follows:

- Case A: High growth
  The future economy and energy system are characterized by high rates of economic growth and rapid 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 the economy and technology and, compared with Case A, strong emphasis on environmental issues and international equity.

In terms of describing the scenarios with the energy systems model MESSAGE, assumptions concerning technological change had to be harmonized with the scenario definition. Figure 2 shows the type of model employed: assuming increasing knowledge and cumulative application and construction of the technology, costs are reduced and performance parameters such as conversion efficiency improve over time [18]. The technology data bank of MESSAGE includes time series with improving performance and decreasing costs for all important technologies, especially new systems like photovoltaic (PV) electricity generation and all technologies related to hydrogen production and use. The rates of change vary across the three cases according to the assumptions made concerning economic growth and technology dynamics.

The modeling process described has a severe shortcoming: the model can (and does) decide to use a technology later in time, after the costs have

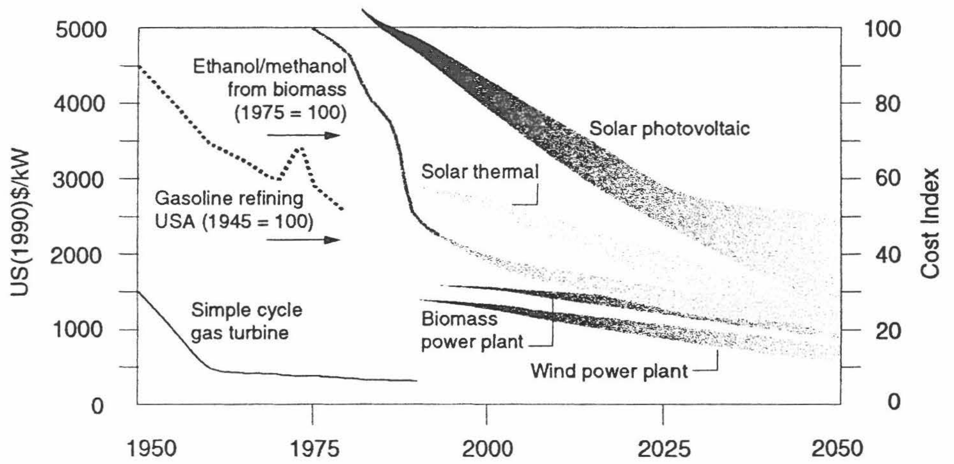

Fig. 2. Examples of historical and assumed future technology cost improvements

declined; thus it can avoid investments during the learning phase of the technology. In this case, technology improvements and learning enter as "free goods". The result is the rather late adoption of new technologies, as deciding on their use occurs only when the technology parameters 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 is not an instantaneous large-scale process; it proceeds gradually, through the progressive exploitation of niche markets. These niche markets, together with continued RD&D, provide for "learning by doing," for example, through the accumulation of knowledge and experience in the manufacture of machines or equipment. Experience is also accumulated in the application of technologies, a process called "learning by using." Knowing how to effectively apply a technology can improve its performance considerably. Additionally, learning by using is an important source of information for improving the design characteristics of new technologies and for making these technologies more economical. Learning is contingent on actual implementation of and experimentation with new technologies; the more implementation and experimentation takes place, the greater the resulting learning and improvements of technologies. Thus, future technology improvements become endogenous aspects of the crucial development process and path; that is, they are a function of the particular development (investment) strategy chosen. A frequently used way to represent this learning process is to express learning (e.g., cost reductions) as a function of cumulative installations (sales or installed capacities of new equipment). The information in Fig. 3 is similar to that given in Fig. 2, but with cumulative investment (or knowledge) measured on the horizontal axis.

Generally, linear programming models such as 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

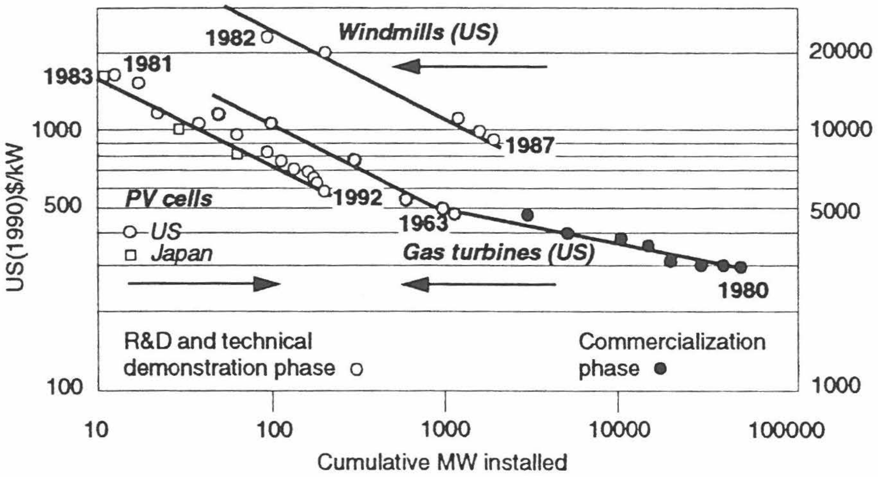

Fig. 3. Technology learning: improvement in the costs of per unit of output versus cumulative output

technological learning, this feature implies that in the linear model the mature technology parameters are available without an investment in the learning process; in other words, there is a direct connection from zero installations to the parameters of the mature technology.

For linear programming models, the standard methodology for coping with non-convex relationships is mixed integer programming (MIP). Like all nonlinearities, non-convex relations are described by stepwise 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 must be paid. A pure linear programming model would permit the use of cheap technologies regardless of the actual market size.

3 The energy model MESSAGE

The energy optimization model MESSAGE is a dynamic linear programming model of the overall energy system. It models flows of energy through the energy system, from primary energy extraction via conversion (e.g., in refineries or power plants) up to final utilization in various sectors of the economy. MESSAGE uses two major types of variables: activity variables describing the fuel consumption of technology j in period t (X_{jt}), and capacity variables for annual new installations of technologies (Y_{jt}). Constraints applied in all modeling exercises concern (a) acquiring sufficient supplies of the (exogenous) demands, (b) balancing quantities for all energy carriers and periods, (c) constraining resource availability, and (d) ensuring the installation of sufficient capacity of the technologies applied. Additional constraints can be defined depending on the needs of the application: for example, the need to limit the market penetration of new technologies or to relate technologies based on energy sources with stochastic availability to a certain share of the overall supply (see [5] for a full description of the mathematical formulation of MESSAGE).

The objective function generally applied in MESSAGE is to minimize the sum of the discounted costs, or the net present value, of the overall energy system. A simplified version of this objective function could be written as

$$min \sum_j \sum_{t=1}^{T} [d_t^o \Delta_t X_{jt} \times i_{jt} + d_t^c \Delta_t Y_{jt} \times o_{jt}],$$

where T is the number of periods in the model; d_t^o and d_t^c are the discount factors applied for operating and capital costs, respectively; Δt is the length of period t in years; and i_{jt} is the specific investment and o_{jt}, the operating costs of technology j in period t. This objective function is minimized subject to the energy balance and demand constraints, where all producers of energy carrier e (technologies in P_e) must supply sufficient energy for either all consumers (technologies in C_e) or for the exogenous demand for e (D_{et}), taking into account the conversion efficiencies of the technologies, (η_{jt}):

$$\sum_{j \in P_e} \eta_{jt} X_{jt} \geq \sum_{j \in C_e} X_{jt} + D_{et}.$$

Capacity requirements are determined by a vintage type of approach, that is, production in a period is related to all capacities up to a certain age (the technical plant life, Π_j), including the contribution of capacities existing before the first modeled year (h_{jt}):

$$\eta_{jt} X_{jt} \leq \alpha_{jt} \sum_{\tau = t - \Pi_j}^{t} \Delta_\tau Y_{\tau j} + h_{jt}.$$

Average utilization of the capacity is described by the plant factor α_{jt}, which is more important for electricity generation than for other technologies. Overall resource consumption is controlled by constraining the quantities extracted over the entire model horizon to the available quantities of a resource (R_j):

$$\sum_{t=1}^{T} \Delta_t X_{jt} \leq R_j.$$

Additional constraints on resource extraction, such as depletion constraints limiting the quantity extracted during a period to the volume still available, or constraints on the growth of extracted quantities, can also be formulated.

The application of MESSAGE is parameterized by a set of input files describing the energy system. There are three types of technology-related parameters: technical parameters like conversion efficiency, technical plant life, and plant factor; economic parameters such as investment and operating costs; and ecological parameters, in most cases emission factors for CO_2, SO_2 and nitrous oxides (NO_x). Other required parameters concern the demands derived from the Scenario Generator in the current application and the availability of depletable and renewable resources. Depending on the scenario, other parameters can be introduced, such as emission constraints or limits on the application of certain technologies.

4 Modeling technological learning

For the first experiments with the endogenized process of technological learning, investment costs were chosen as a dependent variable. Process models like MESSAGE require technology costs as specific values, for example, per kW. In the model formulation, these costs are multiplied by the annual new installations to yield 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. The 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 is the discount factor for period t, Y_t the annual investment in period t, Δ_t the number of years in period t, i_t the specific investment cost in period t, and T the number of periods in the model.

Endogenizing technological learning in a technology-oriented model requires a representation of changes in technology parameters during the learning process. The measure used for cumulative knowledge acquired in the learning process is cumulative installed capacity. Dynamic 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.

As described in the previous section, this non-convex relationship can be formulated using an extension of linear programming, namely, an MIP formulation. In MIP, single variables of the problem can be forced to take only integer values. A special algorithm (most commonly the branch-and-bound method) searches the solution space along the tree of possible decisions for integer variables in order to find the optimal solution. An extension of mixed integer formulations that is useful for the problem investigated here is Type Two Special Ordered Sets (SOS-2). These sets are defined as consisting of at least two variables and having the characteristic that only two adjacent variables can take nonzero values.

By definition, SOSs are very well suited to interpolate non-convex relationships. This suitability is exemplified for the non-convex relationship $y = f(x)$. Each variable in the set (S_i) stands for a cornerpoint in the piecewise linear interpolation of $f(x)$. Because by definition only two adjacent variables can have nonzero values, setting the sum of the SOS variables equal to one provides interpolation along these points. Williams [36] provides a comprehensive explanation of the basic formulation possibilities: Nemhauser and Wolsey [37] describe potential solution algorithms; and Jeroslow [38] goes into more detail with respect to mixed integer formulations.

$$\sum_{i=1}^{n} S_i = 1.$$

Multiplication of the variables in the set (S_i) by the x-values (x_i) provides the x-value,

$$x = \sum_{i=1}^{n} x_i S_i;$$

multiplication by the corresponding y-values (y_i) provides the function value in the MIP formulation

$$y = \sum_{i=1}^{n} y_i S_i.$$

Formulating the cost curve of technological learning using an SOS-2 formulation includes the following steps:

1. Interpolate cumulative investments; that is, determine where in 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. Include the investment variables in the objective function; discounted with a discount rate of 5% per year:

$$\sum_{t=1}^{T} d_t I_t,$$

where S_{nt} are the 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, and i_n represents the interpolation points for average costs.

This formulation is added to the standard formulation of MESSAGE, as it is described in Section 3 and in [5], and solved with a commercial MIP package, CPLEX [39].

5 Application and results

Among the differences between the three families of scenarios described in Section 2 are the different descriptions of technology dynamics over time. Cases A and C have dynamic expectations of potential technology improvements, and Case B presents a more conventional view of the future, with 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, that is, estimates of present costs for new installations, and the costs in 2050 for Cases A and B. These cost estimates were based on data collected in CO2DB, the IIASA CO_2 mitigation technology inventory [40]. A statistical analysis of these underlying data is described in [41].

Table 1. Investment costs and progress ratios of selected technologies, in US dollars (at 1990 value) per kW

Technology	1990	2050		Progress ratio
		Case B	Case A	
CoalAdv	1,650	1,500	1,350	0.93
GasCC	730	600	400	0.85
NewNuclear	2,600	2,300	1,800	0.93
Wind	1,400	900	600	0.85
SolarTH	2,900	1,600	1,200	0.85
SolarPV	5,100	2,000	1,000	0.72

Table 1 shows that in the Middle Course, Case B, the potential for improvements for advanced coal and new nuclear technologies is assumed to be in the range of 10% ; gas combined cycles improve by nearly 20%; and the cost reduction potentials for the renewable technologies are highest, with 35% for wind, 45% for solar thermal, and 60% for PV electricity generation. In the case with more dynamic technological change, Case A, the potentials for improvements lie between 18% for advanced coal-based electricity generation and 80% for solar PV. These cost reductions change the cost rankings of the technologies. 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 11 world regions. For each region, 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 entire system is solved simultaneously. This world energy model, M11T, has on the order of 35,000 variables and 50,000 constraints, depending on the case, that determine the number of new technologies available in the system.

A smaller version of the world model was developed for additional investigations and for the development of new methodological approaches. This small version, CWM, consists of only one region depicting the world as a whole and currently does not include end-use technologies, but rather includes demands for types of final energy carriers (gaseous, liquid, solid, electricity, and district heat). CWM is used for the initial experiments with the approach to internalizing technological learning used in MESSAGE III. Its model size is approximately one-tenth that of the full model, with 2,700 columns and 3,400 rows.

Technological learning in terms of the reduction of investment costs as a function of cumulative installations is included in 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 five can be reached; the reduction potential for gas combined cycles is approximately 45%, from US$730/kW to US$400/kW. The maximum potential degree of cost reduction is limited in this application for methodological reasons: in order to evaluate how the option of influencing the speed of technological progress affects the results, other differences that could come from different absolute cost levels are excluded. Table 1 also shows the progress ratios used in the analysis. Generally, for more mature technologies, lower progress was assumed, while for newer technologies the progress ratios of 0.85 are between high and average values for large plants, as shown by Christiansson [42]. The implied cost reduction per doubling of capacity is 7% for mature technologies and 15% for new technologies. This diversification is inspired by Fig. 3, where the exponential decrease of cost as a function of overall installed capacity occurs when technologies become more mature, that is, when the potential for improvement declines. For PV cells, which can be grouped into technologies with modular design, an even higher reduction potential with a progress ratio of 0.72 (a 28% cost reduction per doubling) is assumed. As for the large plants, this value lies in the range of high and average progress ratios for modular technology designs.

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 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 in 1990 includes 38% coal, 14% gas, 17% nuclear, and 30% other sources (predominantly hydropower), undergoes a major shift toward nuclear energy; by 2050, 55% of all electricity is generated from nuclear energy. The second-largest share (33%) is from coal-based systems, with standard coal-fired power plants increasing their

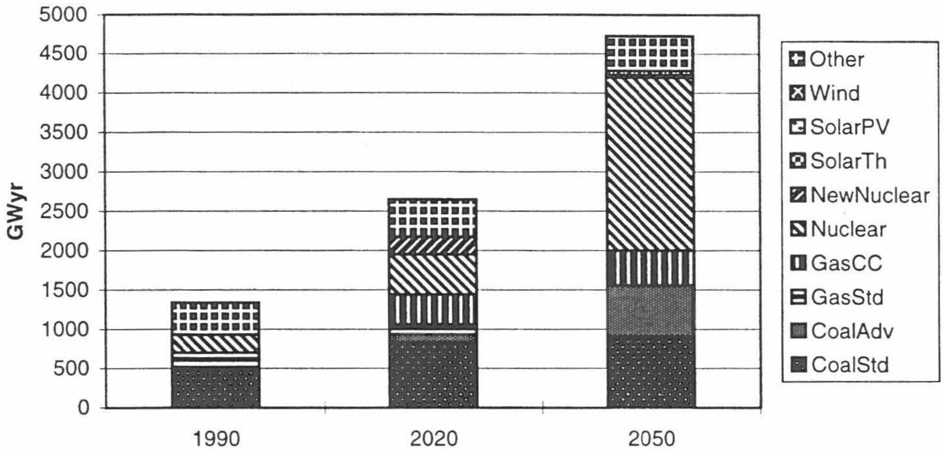

Fig. 4. Electricity generation in the static case, 1990, 2020, and 2050

production from current levels of 515 GWyr to 911 GWyr, and advanced coal-based systems supplying an additional 641 GWyr by 2050. Gas-based electricity generation in steam turbines (184 GWyr in 1990) is virtually phased out by 2050, and 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 US$38 per barrel of oil equivalent (boe) in 2030]. Solar thermal systems are first used in 2050, but their contribution is below 1%. PVs do not become competitive at the energy prices prevailing in this scenario.

The static case, as presented here, represents a scenario where resources are dwindling: 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 economical 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 picture changes dramatically with the introduction of technological learning, as described in Section 4, for the electricity generation technologies listed in Table 1 (see Fig. 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), and new technologies, which have the potential for technological learning, expand considerably. Wind generators, solar electricity generators, and new nuclear generators are employed, and the use of advanced coal-based systems also increases slightly. In 2020 two changes can be observed, namely, the initial 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 share of coal in electricity generation is 17%, versus 33% in the static case; nuclear energy supplies 36% of total electricity, compared with 46% in the static case; and solar PV contributes 19% and wind energy 10% of electricity generation, compared with 0.7% and 1%, respectively, in the static

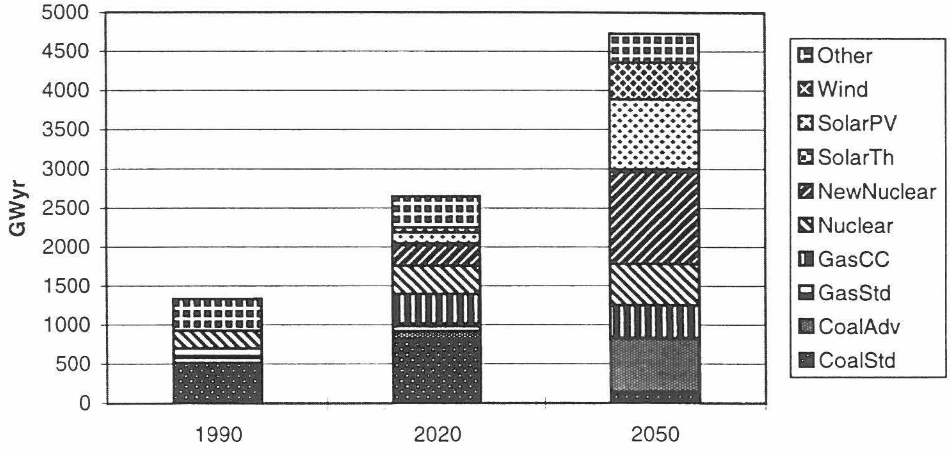

Fig. 5. Electricity generation in the case with technological learning in electricity generation, 1990, 2020, and 2050

case. The effect of technological learning on marginal production costs (or shadow prices) leads to stable electricity prices, compared with a 13% increase of marginal costs in the static case.

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

Because increases in the price of natural gas due to the depletion of easily accessible reserves have a major effect on model results, a logical next step in model development is to extend the technological learning principle to extraction technologies. The assumption in Case A concerning technological learning in oil and gas extraction (applied only to the more expensive categories) is that a 40% reduction could be achieved up to the year 2050. This assumption is incorporated into the small world model as a potential cost reduction.

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

The electricity generation pattern in 2020 (see Fig. 6) is not significantly different from that of the previous case, but by 2050 the contribution of gas-based combined cycles reaches a higher share than in either of the other cases, accounting for 36% of electricity. This expansion is reached at the expense of nuclear energy (no standard nuclear systems are used and the advanced systems contribute 25% less) and advanced coal (which contributes only 4%, compared with 15% in the previous case).

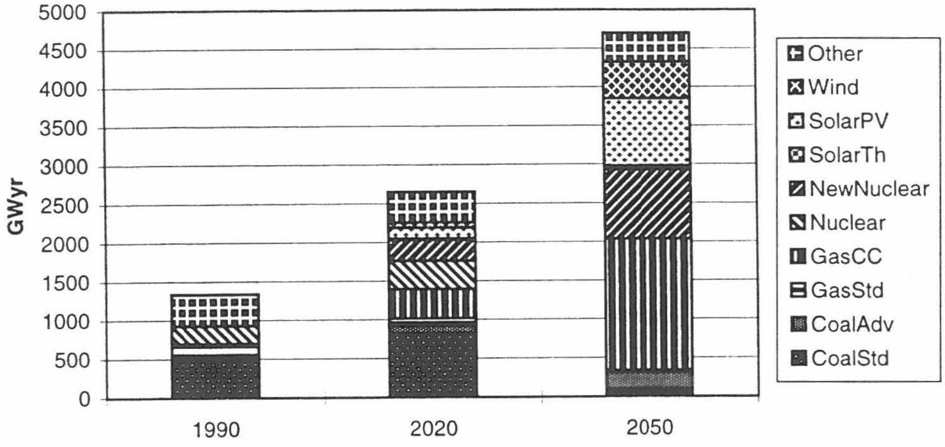

Fig. 6. Electricity generation in the case with technological learning in electricity generation and extraction, 1990, 2020, and 2050

6 Comparison with standard applications

The analyses in Section 5 have shown that modeling technological learning in terms of cost reductions with growing experience dramatically influences model outcomes. In this section, this approach is compared with the use of dynamic parameters, 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 of investment costs described in Table 1 by 2040. Figure 7 compares the electricity generation patterns in 2050 for this case (labeled dynamic) with those for 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% and standard nuclear

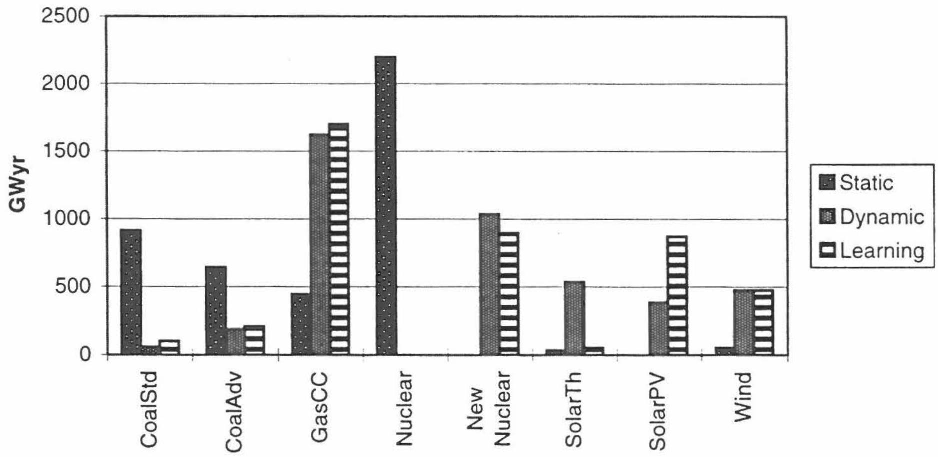

Fig. 7. Electricity generation in 2050 by case and technology

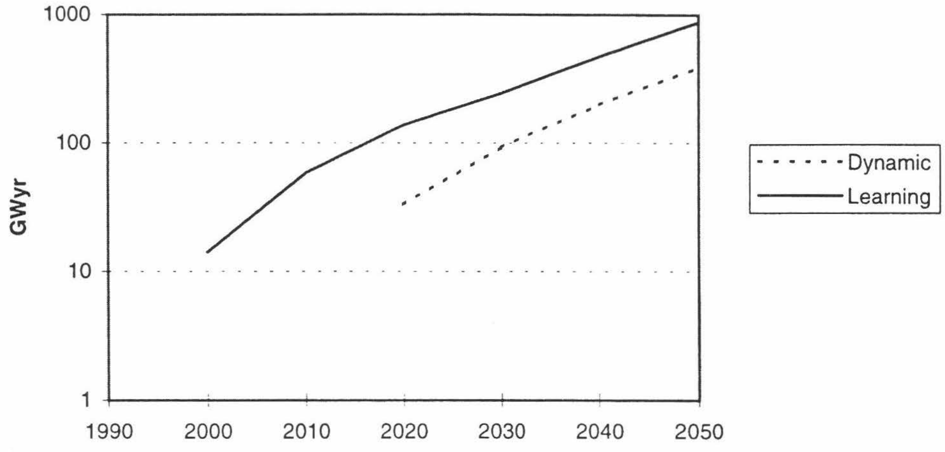

Fig. 8. Electricity generation from solar PV in the dynamic and learning cases, 1990 to 2050

technologies are phased out and partly replaced by new 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 starts to penetrate the market.

Comparing the dynamic case with the learning case shows some small differences, as well as one major dissimilarity concerning solar electricity generation. Overall, solar electricity generation is the same, but in the learning case nearly all of it comes from PV, while in the dynamic case some 60% is still from thermal systems. This is an effect of the crossing over of the cost curves of the two solar electric systems. This crossover occurs at a fixed point in time in the dynamic case, but in the learning case its timing can be influenced by higher investments in PV systems. Consequently, with endogenized learning, PV penetration starts as early as 2000, compared with 2020 in the dynamic case, and penetration rates are much higher (see Fig. 8).

The specific investment costs per kW installed for solar PV systems in the dynamic and learning cases are compared in Fig. 9. The assumption in Case A, the dynamic case, is a linear cost decrease over 50 years of 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 nonlinear. The initial small reduction of 10% between 1990 and 2000 is followed by a major reduction in costs of more than 50% by 2010. Between 2010 and 2020 there is another significant decrease in costs, amounting to a 40% reduction. The final reduction, occurring between 2020 and 2030, is again around 10%.

Similar comparisons can be made for all technologies. One interesting case is that of advanced coal, shown in Fig. 10. Initially, no investment takes place in this system; therefore, in the learning case, costs are not reduced up to 2000. Specific investment costs start to decrease slowly up to 2010 and thereafter accelerate until, by 2030, they have reached the ultimate level of cost improvements. In the dynamic case, on the other hand, cost improvements are predefined by a given pattern over time. Although

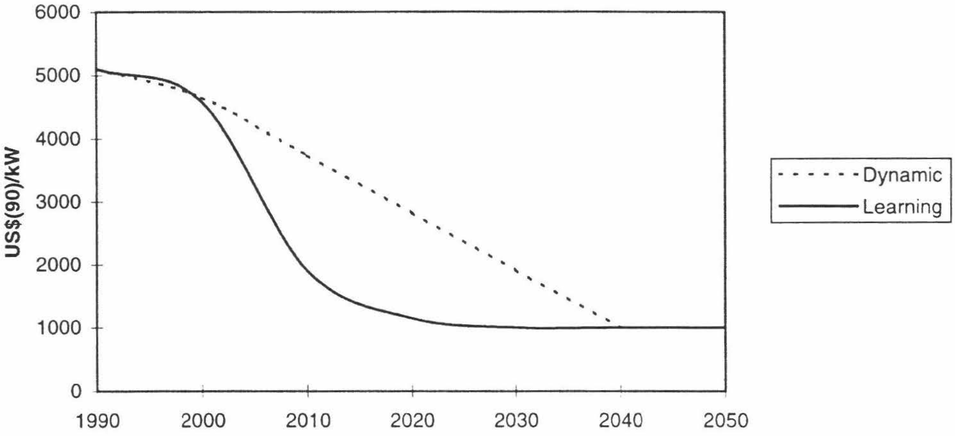

Fig. 9. Specific investment costs for PV systems in US dollars (at 1990 value) per kW for the dynamic and learning cases, 1990 to 2050

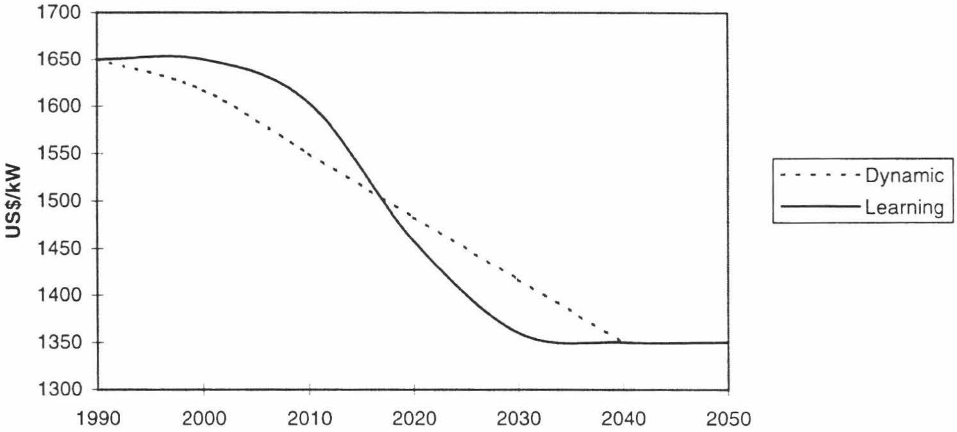

Fig. 10. Specific investment costs for advanced coal power plants in US dollars (at 1990 value) per kW for the dynamic and learning cases, 1990 to 2050

investments in advanced coal systems start only in 2010, parameters improve in a static manner over time.

Figure 11 shows the effect of making investment costs dynamic (dynamic case) and endogenizing technological learning in terms of investments (learning case) by comparing the investment profiles for these two cases with that of the static case. Investments in the energy sector today account for at least 10% of international credit financing, which currently is around US$3.6 trillion ($10^{12}$) [43]. In the static case, the annual energy investments increase at an average annual rate of 2.4%, growing to 4.2 times the 1990 level by 2050. This trajectory is taken as basis for the comparison in Fig. 11 and is shown as 100% there. If specific investment costs of new technologies decline over time (dynamic case), the overall investments start at a higher level than in the static case in order to initialize faster market penetration of the new technologies, which reduces investments by up to 20% after 2020.

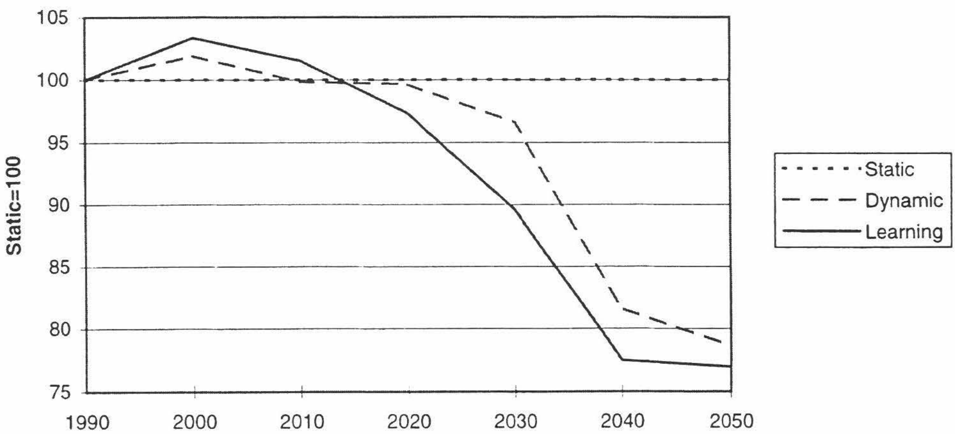

Fig. 11. Annual investments in the dynamic and endogenized learning cases compared with those in the static case, 1990 to 2050

In the case with endogenized technological learning, investment in expensive technologies such as solar PV starts earlier, as was shown in the previous analysis. Consequently, overall investment is 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 with the dynamic case. Up to 2020, cumulative investments in the energy sector are 0.2% higher in the dynamic case and 1.5% higher in the endogenized technological learning case than in the static case. Between 2020 and 2050, both the dynamic and learning cases show reductions in cumulative investments; however, the reductions are 50% greater in the case with endogenized technological learning (−13.2% compared with the static case) than in the dynamic case (−8.7% compared with the static case). Over the entire time horizon, 1990–2050, cumulative investments are 6.6% lower in the dynamic case and 9.7% lower in the endogenized learning case than in the static case. 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 is modeled in the dynamic case.

The objective function of the optimization runs is the sum of all discounted costs (or the net present value) of the energy system over the entire horizon up to 2050, using a discount rate of 5%. In the static case, the objective function value is US$186.2 trillion ($10^{12}$) in 1990 dollars [US$(90)]. In the dynamic case it is reduced by US$(90)1.79 trillion, and in the endogenized learning case it is reduced by US$(90)2.22 trillion, some 24% more.

In this modeling approach, which minimizes the overall discounted cost, the factor that influences investments the most is the discount rate chosen for the analysis. In this approach, capital is available at a cost that exactly matches the discount rate, so the discount rate defines the interest paid on capital. Thus, it is clear that higher discount rates tend to favor technologies with lower up-front investments, even if the operating costs are higher, whereas low discount rates result in increased use of technologies with high initial investment. The results of sensitivity analyses of MESSAGE to the discount rate have shown that renewable technologies, which have comparatively high investment requirements, tend to be used more at lower discount rates (see [44]). Consequently, an analysis of the influence of the discount rate on the results presented here would show a faster introduction of solar PV at low discount rates and a slower introduction at high discount rates. Thus, it is important to state that both the dynamics of technological learning and the choice of the discount rate play an important role in determining the shape of the development trajectories.

7 Conclusions

Technological learning has been endogenized into 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 when endogenized learning, rather than static model parameters, is used. In contrast 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 result 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, whereas in the case of a trajectory for system cost, a share of 8% of electricity generation by PV is reached by 2050. By endogenizing the process of knowledge accumulation and cost reduction into 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: In the learning case, cumulative investments are reduced by 13% compared with the static case and by approximately 5% compared with the dynamic case. However, endogenizing technological learning also reduces the overall discounted costs of the energy system by 1.2% compared with the static case, which is 0.2% more than the dynamic case. Compared with the static case, the overall cost reduction is US$(90)2.2 trillion. The basic message from this experiment is that early decisions concerning the introduction of new technologies are essential for reaching good economic performance over time.

Technological learning, as implemented in the current approach, includes only expenditures made during the time a technology is actually applied. RD&D expenditures, be they for scientific research or development and demonstration by a company, are not explicitly incorporated. In an early attempt to introduce induced technical change in a linear programming model, Nordhaus and Van der Heyden [45] included the up-front investments for R&D by using an integer variable indicating whether or not

[7] The discount rate used for this analysis is 5% , as was used in the underlying IIASA-WEC study [18].

R&D takes place. In this case, a new technology can only be applied if this up-front investment is made. Future enhancements of the modeling approach presented here will include a representation of up-front R&D along these lines.

As already postulated by Schumpeter [46], technical change is an evolutionary process with considerable uncertainties involved in all stages. The modeling approach presented in this paper is an initial step toward endogenizing the process of technological learning into energy systems modeling. Under the conditions of optimal technology selection and for the setup and parameters of the model chosen, this approach gives answers to questions concerning optimal allocation of research funds and R&D expenditures. In real life, where "technological innovations would consist mostly of non-starters" [47], the winners and losers are not known at the outset. What is therefore required as an addition to this initial experiment is the further expansion of the approach to deal with uncertainties concerning the success of new technologies, as well as the uncertainties concerning the development paths that technology performance takes. An initial step in this direction has been taken by introducing the uncertainties of future technology performance as such into the model formulation [48]. Early experiments with the stochastic version of MESSAGE have shown that, if the uncertainties concerning future technology performance are incorporated, the model tends to spread risk over more technologies. Combining the two approaches – endogenizing the process of technological learning and incorporating uncertainties concerning the degree of possible learning – would then also hedge against the risk of wrong investment strategies by diversifying into the most promising options. The combined approach would quantify the expenditures that still lead to an optimal allocation of financial resources, depending on the risk perception of the decision maker. Although it clearly could not tell which technologies will be the winners in the future, it could mark clusters of technologies with certain characteristics for which research funds should be spent.

The results presented in this paper have some important implications for energy policy. They clearly show that it is misleading to simply model new technologies as future "back-stops" that will at some point become available at lower costs. This approach leads to postponed investment in these technologies, and implies that it would be opportune to wait until new technologies become cheaper. However, these new technologies will never become cheaper without determined RD&D policies. Furthermore, investments in new technologies are uncertain and costly, because there are many "non-starters". This paper has shown that the first step in endogenizing technological dynamics indicates that up-front investment and determined RD&D policies can lead to future cost reductions and technology performance improvements. Further work is required to include technological uncertainty as another important property of technology development.

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