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# ENDOGENOUS TECHNOLOGICAL CHANGE IN ENERGY SYSTEM MODELS

## Synthesis of Experience with ERIS, MARKAL, and MESSAGE


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## Preface

This report summarizes Activities 1.4 ‘Common techniques for incorporation of endogenous technology evolution in the large scale models’ and 2.3 ‘Experience from MARKAL and MESSAGE’ of the TEEM project. It brings together the experiences and insights gained by the project partners PSI (Switzerland), IIASA (Austria) and ECN (project number 7.7126). The contribution to this project has been carried out on behalf of the European Union (in the framework of the Non Nuclear Energy Programme JOULE III), contract JOS3-CT97 0013).

## Abstract

Technological change is widely recognised as a key factor in economic progress, as it enhances the productivity of factor inputs. In recent years also the notion has developed that targeted technological development is a main means to reconcile economic ambitions with ecological considerations. This raises the issue that assessments of future trajectories of for example energy systems should take into account context-specific technological progress. Rather than taking characteristics of existing and emerging technologies as a given, their development should be a function of dedicated Research, Development and Demonstration (RD&D) and market deployment under varying external conditions.

Endogenous technological learning has recently shown to be a very promising new feature in energy system models. A learning, or experience curve, describes the specific (investment) cost as a function of the cumulative capacity for a given technology. It reflects the fact that technologies may experience declining costs as a result of its increasing adoption into the society due to the accumulation of knowledge through, among others, processes of learning-by-doing and learning-by-using.

This report synthesises the results and findings from experiments with endogenous technological learning, as reported separately within the EU TEEM project. These experiments have been carried out by three TEEM partners using three models: ERIS (PSI), MARKAL (ECN and PSI), and MESSAGE (IIASA). The main objectives of this synthesis are: to derive common methodological insights; to indicate and assess benefits of the new feature, but also its limitations and issues to solve; and to recommend further research to solve the main issues.

This synthesis shows that all model applications are examples of successful first experiments to incorporate the learning-by-doing concept in energy system models. Incorporating the learning-by-doing concept makes an important difference. The experiments demonstrate and quantify the benefits of investing early in emerging technologies that are not competitive at the moment of their deployment. They also show that the long-term impact of policy instruments, such as $CO_2$ taxes or emission limits and RD&D instruments, on technological development can be assessed adequately with models including technology learning.

Adopting the concept of endogenous learning, several types of RD&D interventions can be addressed that aim at accelerating the market penetration of new technologies. The directions into which such interventions might lead have been illustrated in some of the experiments. However, quantitative relationships between R&D policy and learning data parameters are still unknown

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# 1. INTRODUCTION

Technological change, also referred to as technological progress, is widely recognised as a key factor in economic progress, as it enhances the productivity of factor inputs. In recent years also the notion has developed that targeted technological development is a main means to reconcile economic ambitions with ecological considerations (see, for example, Grübler, 1998a). This raises the issue that assessments of future trajectories of for example energy systems should take into account context-specific technological progress. Rather than taking characteristics of existing and emerging technologies as a given, their development should be a function of dedicated RD&D and market deployment under varying external conditions. Internally consistent frameworks incorporating appropriate links with technological change, including learning rates and technology maturing costs receive increasing attention.

Elaborating the general concepts, endogenous technological learning has recently shown to be a very promising new feature in energy system models. This paper synthesises the results and findings from four experiments with endogenous technological learning, as reported within the EU TEEM project. These experiments have been carried out by three TEEM partners using the models ERIS (PSI), MARKAL (ECN and PSI), and MESSAGE (IIASA). The experiences of the teams have been reported separately in more detail (Kypreos and Barreto, 1998a (ERIS), 1998b (MARKAL); Seebregts, Kram, Schaeffer, and Stoffer, 1998 (MARKAL); Messner and Schrattenholzer, 1998 (MESSAGE).

The objectives of this synthesis paper are the following:

- To derive common methodological insights from these experiments.
- To indicate and assess benefits of the new feature, but also its limitations and issues to solve.
- To provide recommendations for proper use of the new feature.
- To recommend further research to solve the main issues identified.

## 2. THE CONCEPT OF TECHNOLOGICAL LEARNING

Typically, energy scenarios analysed with energy system models assume that characteristics of technologies can change over time. This can be seen as a reflection on technology dynamics (learning). However, the trend is often assumed to be exogenous – a function of time, for instance – to the energy system analysis model. This applies to technology cost indicators like the specific investment cost and to performance indicators, e.g. the efficiency of energy technologies.

Recent experiments with the small-scale global energy system model GENIE (Mattsson, 1997, 1998) and the small version of the global MESSAGE model (Messner, 1997) have shown that formulations with endogenous learning are feasible and lead to insights not directly obtainable from the conventional models. The two models mentioned above apply the learning mechanism to the specific investment cost and adopt a *learning or experience curve* approach: the specific investment cost of a 'learning' technology decreases as a function of cumulative capacity ('*learning-by-doing*' mechanism). Other performance indicators remain exogenous to the energy system model. Figure 2.1 shows examples of such learning curves.

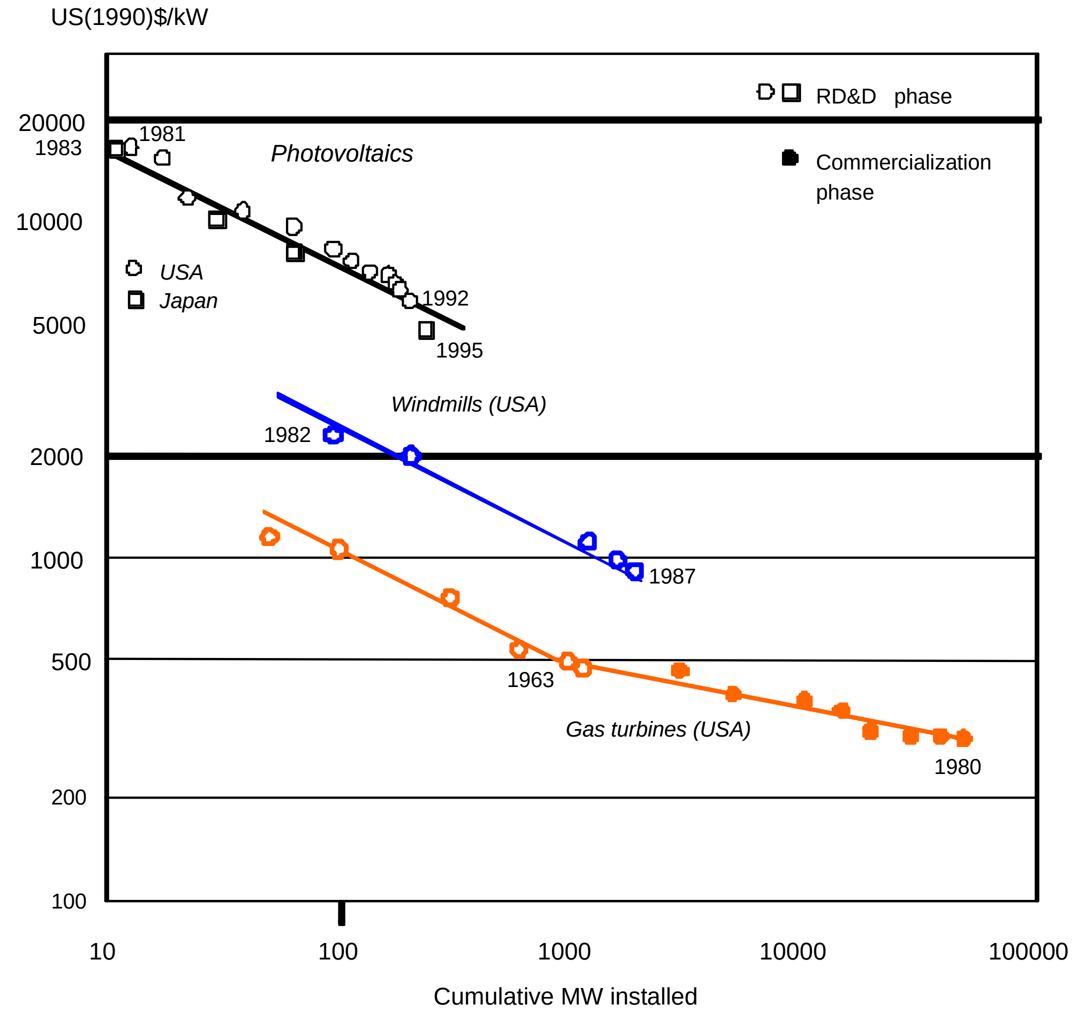


Figure 2.1 *Examples of learning curves of energy conversion technologies*
Source: IIASA-WEC (1998)

A *learning, or experience curve*, describes the specific (investment) cost as a function of the cumulative capacity for a given technology. It reflects the fact that technologies may experience declining costs as a result of its increasing adoption into the society due to the accumulation of knowledge through, among others, processes of *learning-by-doing* and *learning-by-using* (Dutton and Thomas, 1984; Grübler, 1998b). A number of technical, economical, environmental and social factors may also influence the cost reductions. The cumulative capacity is used as a measure of the knowledge accumulation occurring during the manufacturing and use of one technology (Christiansson, 1995). An experience curve can be expressed as:

$$SC(C) = \mathrm{a} \times C^{-\mathrm{b}}$$

Where:

| | |
|---|---|
| *SC* | Specific cost |
| *C* | Cumulative capacity |
| a | Specific cost at C=1 |
| b | Learning index (constant) |
| $C_0$ | Initial cumulative capacity (at t = 0) |
| $SC_0$ | Initial specific cost (at t = 0), equals a × $C_0^{-b}$ |

The *learning index* b can be used to calculate the *progress ratio* or vice versa. The progress ratio (pr) expresses the rate at which the cost declines each time the cumulative production doubles.

$$\mathrm{pr} = 2^{-\mathrm{b}}$$

E.g., a progress ratio of 0.8 means that the costs per unit of newly installed capacity decrease by 20% for each doubling of cumulative installed capacity. The parameter b thus constitutes one of the key assumptions describing technological progress because it defines the speed of learning for the technology. It is important to note that an alternative but equivalent parameter, the *learning rate*, is often used which is defined as '1 - pr'. The advantage of using the learning rate rather than the progress ratio is that a higher learning rate means a faster decrease of costs, while a higher progress ratio means a slower decrease of costs. Despite of this, the use of progress ratios seems more widespread. Table 5.1, Section 5.1 shows some examples of progress ratios used in the various applications summarised in this paper.

# 3. SCOPE AND COVERAGE OF THE MODELS

The purpose of this section is to describe briefly the main characteristics of the four models and applications selected for this synthesis paper. For details, the interested reader is referred to the underlying reports and papers.

## 3.1 ERIS prototype (PSI)

ERIS (Energy Research and Investment Strategy) is a small-scale global energy model prototype specified and developed during the TEEM project. The original purpose of ERIS, as set out in (TEEM, 1997), was to capture the main mechanisms regarding the endogenous analysis of RTD policy under uncertainty and to allow for a consistent cost-benefit analysis of specific policies aiming at technology prioritisation. The original prototype, specified by IIASA (Messner, 1998) and coded by NTUA (Capros et al., 1998), was extended by PSI to include stochastic and more general constraints (Kypreos, 1998). It considered the non-linear programming (NLP) formulation of experience curves. (Kypreos and Barreto, 1998a) describes the implementation of the Mixed Integer Programming (MIP) formulation of learning curves into the ERIS prototype, makes a comparison between NLP and MIP solutions, and examines some parameters affecting the MIP solution. The experience with ERIS reported in (Kypreos and Barreto, 1998a) is used in the underlying synthesis paper. Further development of ERIS by PSI is currently being considered as part of the last phase of the TEEM project.

## 3.2 MARKAL (ECN and PSI)

MARKAL is a widely applied bottom-up, dynamic linear programming (LP) model (Fishbone et al., 1983) developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA). Besides this ‘standard’ MARKAL LP model, which has provisions to model material flows within the energy system and to include uncertainty by a stochastic programming approach, the MARKAL family of models includes (IEA-ETSAP, 1997; DecisionWare, 1998; IEA-ETSAP, 1999):

- The MARKAL-MACRO model, a relatively new (NLP) model that combines the technological detail of MARKAL with the general economics of MACRO, a long-term neoclassical growth model.
- The MARKAL-MICRO (NLP) and MARKAL-ED (LP) models which have a partial equilibrium model not representing the rest of the economic system, but allowing demands to be reduced in response to higher energy prices.

With only a few exceptions, the individual capabilities outlined above are additive in nature, that is they can be used in combination with each other, and are embedded in one software system. For more details, see (IEA-ETSAP, 1997, 1999) or (DecisionWare, 1998).

Experience from MARKAL models with endogenous learning was gained for a small-scale example, the simple global MARKAL model (Kypreos and Barreto, 1998b) and for a large-scale example covering Western Europe (Seebregts et al., 1998). Both examples are used in this synthesis paper.

### 3.2.1 The simple global MARKAL (PSI)

The simple global MARKAL model reported in (Kypreos and Barreto, 1998b) represents the global electricity market. The demand for electricity corresponds to the IIASA scenario B (IIASA/WEC, 1998). In this exercise, competitiveness of different electricity generation alternatives is examined. Six of them are allowed to experience learning in the investment cost, while for the others the cost is assumed constant along the horizon.

### 3.2.2 Large scale Western Europe MARKAL (ECN)

The (standard) MARKAL model application reported in (Seebregts et al., 1998) is the first large scale MARKAL application with endogenous learning. Main objectives were to evaluate whether the MIP formulation is feasible for large scale MARKAL models and to prepare and synthesise methodological recommendations, numerical results and sensitivity analyses and provide them for use in other activities of the TEEM project.

## 3.3 Reduced version of the global MESSAGE (IIASA)

The results of first experiments with endogenous learning in a reduced version of the global MESSAGE III model were reported by (Messner, 1997).The reduced version ('CWM') models the world as one region and includes only final energy demand (and therefore makes no distinction into end-use technologies). The reduced model is about one-tenth of the size of the full MESSAGE model. The paper (Messner and Schrattenholzer, 1998) reports additional experience and is used in the underlying synthesis paper.

## 3.4 Comparison

The comparison of the models with respect to their scope and coverage has been summarised in Table 3.1. The aspects included are:

*Parameters subjected to learning*
All models restrict learning to the specific investment cost.

*Type of model*
All models can be characterised as dynamic, perfect-foresight, cost optimisation models and adopt the MIP formulation to model the concept of learning curves. The difference – and its significance – between the MIP and NLP formulations is explained in Section 4.1. The ERIS prototype also includes an NLP formulation, while the first experiments with MARKAL were performed on the basis of an NLP formulation. NTUA transformed the NLP model also to a Mixed Complementarity Problem (MCP, Capros et al., 1998). The time horizon is 1990-2050 for all models.

*Geographical scale and regional detail*
Except for the standard MARKAL application for Western Europe (referred to as 'MARKAL-Europe' in the rest of this document), all models are global models. On the one hand, this has the advantage of including the world-wide experience. On the other hand, no distinction is made between different regions, e.g. to model spill-over from one region to another. The experience outside the region should not only be restricted to capacity in operation, under construction, or planned but also newly projected e.g. on the basis of energy system model results for other regions of the world (e.g. see the discussion in (Petersik, 1997).

*Complexity and technological level of detail*
As can be seen from Table 3.1, only the MARKAL-Europe application can be considered as a rather technologically detailed, large-scale model. It has the greatest complexity in terms of number of technologies, level of detail in end-use technologies, number of variables and constraints. The number of segments used for the step-wise linear approximation of the cumulative cost curve is a measure for the accuracy of the MIP formulation. The larger the number of seg-

ments, the larger is the number of discrete variables describing the approximation and hence the computational burden to solve the MIP problem.

### *Language and solver used*

ERIS and MARKAL are implemented in the GAMS language, MESSAGE is primarily written in C. PSI and IIASA use CPLEX as solver, while ECN uses OSL. Since the models differ a lot in size and complexity, a comparison with respect to solver, specific solver option and solution times is not sensible. PSI and ECN report that the choice of specific solver options has an impact on the computational performance and even on the solution generated.

Table 3.1 *Summary table depicting the coverage of the four model applications with endogenous learning*

| Aspect | ERIS | global MARKAL | reduced MESSAGE ('CWM') | MARKAL-Europe ('MARKAL-EUR. 1.0') |
|---|---|---|---|---|
| Parameter affected by learning | specific investment cost | specific investment cost | specific investment cost | specific investment cost |
| Type of model | dynamic, perfect foresight, cost-optimisation, MIP and NLP | dynamic, perfect foresight, cost optimisation, MIP | dynamic, perfect foresight, least-cost optimisation, MIP | dynamic, perfect foresight, cost optimisation, MIP |
| Time horizon | 1990-2050 | 1990-2050 | 1990-2050 | 1990-2050 |
| Geographical scale and regional detail | global, as 1 region | global, as 1 region | global, as 1 region | Western Europe, as 1 region |
| Complexity and level of detail | small | small | medium | large |
| number of technologies | 11 | 13 | 77 | 510 |
| number of learning technologies | 5 | 6 | 6 | 3-10 |
| number of energy demands | 1 (global electricity) | 1 (global electricity) | 5 final energy categories | 51 |
| end-use technologies | 0 | 0 | 0 | 331 |
| Size of the MIP problem | | | | |
| number of variables | 751 | 1444 | 2700[3] | 8600[1] / 9400[2] |
| number of constraints | 1315 | 2260 | 3400[3] | 7000[1] / 8400[2] |
| number of segments | 6 | 6-8 | unknown | 6-20 |
| Language and solver used | GAMS and CPLEX 5.0 (LP, MIP) and MINOS5 (NLP) | GAMS and CPLEX 5.0 | C and CPLEX | GAMS 2.50 and OSL 2.1 |

[1] With 3 learning technologies, 6 segments
[2] With 10 learning technologies, 6 segments
[3] 35000 variables and 50000 constraints in the full 11-region MESSAGE (LP model without endogenous learning)

# 4. MIP FORMULATION

This section first describes the reasons for pursuing the MIP approach but also mentions some drawbacks, prior to addressing the numerical results from the reported experiences. Next, it addresses the additional inputs resulting from the MIP formulation.

## 4.1 Rationale

The learning concept as formulated in Section 2 above introduces, obviously, a non-linear relation between model variables. If, as was the case with MARKAL and MESSAGE, the original models are defined as linear models, sometimes including MIP (Mixed-Integer Programming) extensions, an obvious solution possibility is to approximate the non-linear with mixed-integer relations. All three models therefore adopt a Mixed-Integer Programming (MIP) formulation to incorporate technology learning, the feasibility of which was also demonstrated in the GENIE model experiments (Mattsson, 1997). The MIP feature allows to approximate the non-convex objective function by piece-wise linear functions and to use a so-called branch-and-bound algorithm to search the solution space for the optimal solution. For a description of such an approximation see Messner (1997).

The objective function including the concept of technological learning is not only non-linear (leading to an NLP model), it is also non-convex. This means that the function possesses local minima each of which satisfying the usual necessary conditions for minimum values. The additional challenge of finding the lowest of the local minima, i. e., the global optimum, complicates the task of finding the overall solution considerably. In particular this means that there is no practical exact solution method of the problem. The MIP solution suffers from the errors introduced by the approximation and conventional methods to solve the NLP problem cannot be relied upon to find the global – instead of a local – minimum. This and other disadvantages of the NLP approach led to pursue the MIP approach for MESSAGE and MARKAL. In view of the uncertainty concerning the learning rates (see also Section 5.2), the additional error introduced by the approximation of the learning curve is judged to weigh less than the ambiguity introduced by the possibility of not having found a global optimum. Also note that an MCP (Mixed Complementary Problem) formulation has the same disadvantage due to the non-convex character of the model's objective function. Moreover, some NLP solvers cannot handle large-scale model applications (such as MARKAL-Europe).

While the MIP formulation thus seems to be the best practical approach to model endogenous learning in these perfect-foresight, optimisation type of models, it has some drawbacks to take into consideration:

- The increase of the computational complexity compared to the conventional LP model without endogenous learning describing the same energy system.
- The accuracy depends on segmentation of step-wise linearisation of the cumulative cost curve.
- The solution time and the success to find optimal solutions depend on specific solver options, which may be solver and problem specific and may require some experimentation to find optimal and practical settings.

## 4.2 Input parameters to model technological learning

The PSI and ECN MIP formulations require the following input learning parameters:

- Selection of technologies to learn endogenously.
- For each learning technology: cost level in the start year, the initial cumulative capacity available in the start year and the maximum cumulative installed capacity in the end year, and the progress ratio or, alternatively, the learning rate.
- The accuracy of the segmentation e.g. expressed as the number of segments.

The MESSAGE implementation of technological learning makes assumptions about the initial and maximum cumulative capacity input data and the number of segments used for the linear approximation. Initial cumulative capacities are in the range of 10 GW (for wind and solar systems) up to 50 GW (for thermal and nuclear power plants). Maximum cumulative capacities are parameterised to match the levels of learning, i.e. cost reduction, reached in the underlying scenario from IIASA-WEC. Resulting cumulative capacities are between 300 and 800 GW for the 6 technologies. The number of segments for the approximation was chosen to match the degree of learning possible. It is between 3 and 5 segments for the technologies (see Table 5.1).

Besides these specific learning input parameters, the ERIS and MARKAL models use maximum growth factors and constraints to control the penetration of technologies. Moreover, ECN mentions the use of capacity and investment bounds as other means to prevent seemingly unrealistic penetration rates. In MESSAGE, the compact world model CWM used for this analysis had been parameterised to be capable to mimic the IIASA-WEC scenarios, which have been developed with an 11-region model. The 6 IIASA-WEC scenarios can be represented in CWM by merely changing the scenario assumptions, i.e. demand data, resource availability and cost assumptions, as has been done to model the 6 scenarios with the 11 region world model. This approach resulted in a well-tuned model that uses bounds, market penetrations and additional complex constraints, where applicable to achieve realistic results.

## 4.3 Accuracy of segmentation

The PSI and ECN reports on ERIS and MARKAL discuss the effect of different levels of accuracy for the linear approximation of the cumulative cost curve. Also IIASA considered segmentation as an important point from the outset, especially with respect to learning potential and consequently the number of doublings of cumulative knowledge reachable. Because the initial part of the curve was regarded as more important, the natural subdivision into doublings was chosen for setting the segments. The number of segments was tailored to the learning potential of each technology.

The important point regarding the segmentation is to take into account that the cost reductions are very significant for the first installed units, but afterwards, the learning effect decreases and begins to saturate. Therefore, very likely more segments will be required for the first, rapid-change, zone of the cumulative cost curve. Both the PSI and ECN formulations allow both for such a segmentation scheme.

## 4.4 Formulations compared

The formulation of the ERIS prototype prepared by IIASA reflects the model features of the implementation in MESSAGE. The PSI MIP formulation embedded in the ERIS prototype (Kypreos and Barreto, 1998a) is basically identical to the MARKAL formulations. The most recent PSI MARKAL experiments (Kypreos and Barreto, 1998b) mention a few improved features not yet available for the ECN experiments, such as:

- Dependency of the number of segments on the technology, enabling a technology with large learning potential to be modelled more accurately without sacrificing overall computational complexity.
- A two-stage learning curve model, based on the assumption that progress ratios differ along different stages of the life cycle of a technology e.g. faster learning in the R&D phase and a slow down in the demonstration and market penetration phase. After a certain a threshold capacity for this behaviour, the progress ratio switches to another one.

## 4.5 Issues arising from the various model formulations

Independent from issues arising from the inputs to or the numerical results of the various models' applications (Section 6), the differences in the formulations raise the following issues:

- Should the investment cost of a 'learning' technology have a lower limit (asymptote)? Note that in a finite time horizon, progress ratio, initial cost, initial and maximum cumulative capacity determine a minimum value of specific investment costs. See also Section 5.
- Should maximum growth rates or other bounds for controlling the penetration of new technologies be defined (from: global MARKAL and MARKAL-Europe)?
  The implementation of the learning concept as such will make the inclusion of bounds and market penetration constraints even more important, because otherwise, an optimal solution would always go into the most promising technology alone. In this case this technology would learn most and costs would be the lowest. The model would not hedge at all against uncertainties with regard to the learning of this technology. Note that first MESSAGE experiments with stochastic programming (Gritsevskii, 1998) suggest that the hedging inherent in this approach leads to a smoother and more realistic substitution of technologies than conventional perfect-foresight models.
- Should the learning curve be split into two or more stages, in particular for new, currently non-competitive and marginally applied, technologies (from: Kypreos and Barreto, 1998b)?
  The conclusion of PSI was that a two-stage learning model may be useful in specifying realistic limits of the cost reduction, without imposing a fixed lower bound that rules out the possibility of further learning for a particular technology. Note that this deterministic two-stage learning curve could be transformed into a two-stage stochastic learning curve (see also Mattsson, 1998).

# 5. TECHNOLOGY CHARACTERISATION WITH RESPECT TO LEARNING

In principle, endogenising the concept of learning requires selection of learning rates for all technologies. These can be zero for those technologies, for which learning is considered non-essential, given the model run(s) in question. This will focus the analysis and reduce the computational effort to solve the model. In any case, an update of technology characterisation within the model database should be considered to facilitate the storage of – historical or estimated future – progress ratios.

## 5.1 Selection of technologies with endogenised learning

The experiments reported here are primarily focussed on gaining experience from incorporation of endogenised learning into energy models. The selection of technologies with endogenised learning is not always assessed systematically. Table 5.1 in the next Section 5.2 gives an overview of selected technologies and progress ratios applied for the model experiments considered. Solar cells and wind power are for all experiments seen as technologies for which endogenisation of learning could be appropriate and beneficial for modelling purposes.
In the MARKAL-Europe experiments the number of technologies with endogenised learning has been limited to three technologies, which saves computational performance. However, model runs using ten technologies with endogenised learning have been carried out as well. The MARKAL-Europe report identifies the following technology selection criteria:

- large potential of technology learning (reduction of investment costs),
- large expected impact of technology learning on model outcomes,
- a *key technology* within prospective energy systems,
- presence of a direct competing technology with endogenised learning.

E.g., solar cells and wind turbines match these selection criteria, while endogenisation of technology learning for solar cells necessitates also the incorporation of learning for wind turbines, since both technologies are direct competitors on the renewable electricity market. Furthermore, solar cells and wind turbines can be seen as key technologies, i.e. technologies, which are clearly distinct with respect to the applied energy conversion process. They form an essential part of several technology descriptions in energy model databases.

## 5.2 Determination of learning parameters

The learning curve formulation requires additional data on the following 'learning parameters' (see also Section 2 and 4.2):

- Progress ratio (pr) of the technology, or its equivalent learning index (b= -log(pr)/log(2)), or the learning rate (1-pr).
- Initial specific investment costs ($SC_0$) of the technology in start year.
- Initial cumulative installed capacity ($C_{k,0}$) of the technology in start year.
- Maximum cumulative installed capacity ($C_{k,max}$) of the technology over the entire time horizon.

The maximum cumulative installed capacity is strongly related to physical bounds on the installed capacity or ideas on the maximum market share in the end year. It determines the learning potential, here defined as the lowest achievable investment cost level ($pr^n$). Table 5.1 shows that in the various model experiments quite different assumptions on the learning potential are included.

Table 5.1 *Progress ratio (pr), maximum amount of doublings (n) and lowest achievable investment cost level ($pr^n$) compared to initial cost; period 1990-2050*

| | MARKAL Europe[1] | | | MARKAL global | | | reduced MESSAGE global | | | ERIS global | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | pr | n | $pr^n$ [%] | pr | n | $pr^n$ [%] | pr | n | $pr^n$ [%] | pr | n | $pr^n$ [%] |
| advanced coal | × | × | × | 0.94 | 4 | 78 | 0.93 | 3 | 80 | 0.95 | 8 | 66 |
| gas combined cycle | × | × | × | 0.89 | 4 | 63 | 0.85 | 4 | 52 | 0.88 | 8 | 36 |
| new nuclear | × | × | × | 0.96 | 15 | 54 | 0.93 | 5 | 70 | × | × | × |
| fuel cell | 0.82 | 11 | 11 | 0.87 | 13 | 16 | × | × | × | 0.82 | 17 | 3 |
| wind power | 0.90 | 6 | 53 | 0.89 | 9 | 35 | 0.85 | 5 | 44 | 0.88 | 13 | 19 |
| solar PV | 0.81 | 11 | 10 | 0.81 | 13 | 6 | 0.72 | 5 | 19 | 0.85 | 16 | 7 |
| solar thermal | × | × | × | × | × | × | 0.85 | 5 | 44 | × | × | × |

[1] ECN also used 5 and 10 learning technologies, with the progress ratios for these additional technologies equal to the comparable MESSAGE technologies. A detailed assessment has been performed to generate the values of the three technologies included in this table.

Learning-parameter data of technologies, which are already operational, could be derived from historical statistics. As outlined in (Seebregts et al, 1998), historic data is always available, but great care must be applied before historical can be extrapolated into the future. As the variety of progress ratios in Table 5.1 already suggests, the estimation of progress ratios is not always a trivial task. Analysis of the value of historical data for the determination of progress ratios in the future requires a deeper analysis of the dynamics of technological development, allocating the main factors influencing technology learning. Technology learning often shows different phases, for instance a phase which combines large technology improvements, but limited market penetration (technologies in R&D-oriented phase), and a phase were technology improvement is mainly driven by market penetration. Market-oriented phases can be followed by R&D-oriented phases, and the other way around (see e.g. OECD, 1992). Extrapolation of data from one phase (of for instance the R&D-oriented phase in the 1980's on solar cells) could lead to an overestimation or underestimation of the future progress ratio. In order to characterise technological development and to determine the value of progress ratios to be included in a model for a technology, four basic questions should be answered (Seebregts et al., 1998, Chapter 3):

- Is there a historical trend from which a historical progress ratio can be determined?
- Is it plausible that the technology will continue to be developed at all?
- Will the direction of the development remain the same or will its course be altered?
- Is it plausible that the progress ratio observed will stay the same, or will it decrease/ increase?

If the first question cannot be answered positively, the assessment of proper progress ratios could be made by comparison with existing technologies. The remaining three questions are related to the degree of stability of technological development. Several indicators can be defined to measure the so-called system and convergent stability of a technology. Indicators provide guidance as to whether continuation of the historical, higher or lower progress ratios will be the best estimate for the future. The approach above has been followed for the three selected technologies (see Table 5.1, MARKAL Europe).

## 5.3 Clustering technologies and identifying key technologies

On the one hand, the availability of (historic) accurate progress ratio data call for a high level of aggregation, while, on the other hand, modelling an energy system accurately may call for a lot of technological detail, depending of the purposes and uses of the energy system model. If the future of a specific type of a technology is the subject of the forecasting exercise, then a considerable level of detail should be used. If the purpose is to get insights in the future emission of polluting gases, then such a level of detail is not needed. Instead of forcing oneself to choose for instance between solid oxide fuel cell (SOFC) or molten carbonate fuel cell (MCFC) based biomass plants in the future, this future device can also be described as a fuel cell-based biomass plant, without having to make a decision whether the one or the other fuel cell type will be used in this specific application. Shifting from one type to another, resulting in better performances or lower costs can be conceived as a form of learning. The strength of the learning approach relies on the fact that no detailed predictions have to be made about how lower costs or better performance will be reached, but only that these improvements can be achieved.

ECN has termed the issue of less or more technological detail and the mutual consistency of technologies belonging to the same class or cluster of technologies '*endogenous alignment*' (Seebregts et al., 1998). An approach that could be taken to achieve endogenous alignment of technology characteristics is to define '*key technologies*'. Key technologies have been defined in (Seebregts et al., 1998) as technologies that are a component in many other technologies in the database of the technology characterisations of the RES modelled. Examples of key technologies are gas turbines, fuel cells, photovoltaic modules, wind turbines, burners and boilers. Most of the about 500 technologies defined in the MARKAL-Europe database are composed of about 20 of such key technologies. Prior to defining the key technologies, the existing technologies need to be grouped into *cluster of technologies* which are similar with respect to their learning behaviour i.e. the development of these technologies is in some way linked to each other.

# 6. INSIGHTS FROM NUMERICAL RESULTS

## 6.1 Overview of cases

Several model experiments have been conducted to analyse the impact of endogenised learning of selected technologies on model outcomes (see Table 6.1). The focus is to compare and synthesise the methodological insights in order to provide a clear picture of the benefit introduced by technological learning. Comparison of the numerical results of the different models is not the aim, since model coverage (see also Table 3.1) and exogenous assumptions on technology development are diverse.

Table 6.1 *Overview model experiments*

| | MARKAL Europe | MARKAL global | reduced MESSAGE global | ERIS global |
|---|---|---|---|---|
| base case exogenous learning | declining investment costs | constant investment costs | constant + linearly declining investment costs | constant investment costs |
| base case endogenous learning | learning parameters technology specific | maximum cumulative capacity for all technologies at 3000 GW | learning parameters technology specific | maximum cumulative capacity for all technologies at 30000 GW |
| | growth constraint on learning technologies of 20% per year | growth constraint on learning technologies of 5-10% per year | | |
| $CO_2$ reduction cases | 2 | 1 | 0 | 2 |
| R&D and sensitivity cases | progress ratio, initial investment costs, initial cumulative capacity, maximum cumulative capacity | (two-stage) progress ratio | | maximum cumulative capacity, NLP vs. MIP |
| | segmentation (accuracy of approximation cumulative cost curve) | sensitivity on growth rate | | segmentation (accuracy of approximation cumulative cost curve) |

Special cases considered are a comparison of MIP and NLP formulations (ERIS, Kypreos and Barreto, 1998a) and an exogenous learning case with a full scale model using outcomes on the development of specific investment costs of the reduced model including endogenous learning (MESSAGE global, Messner and Schrattenholzer, 1998).

## 6.2 Methodological insights

### *Technology maturing costs incorporated in an integrated fashion*

The experiments demonstrate that future costs revenues by initially non-competitive additional investments are adequately foreseen by the models. E.g. Figure 6.1 shows that endogenisation of technology learning (Case T) induces early investments in initially expensive technologies, since future revenues in the long run are foreseen to offset these short term additional investments. As such, the 'technology maturing costs' are directly incorporated in an integrated fashion. This phenomenon is more pronounced in Case T than in a dynamic case where technology learning is exogenously set by the model user (Case D). Figure 6.1 illustrates that it can be optimal to invest early in technologies, that is, even at a time when they are not competitive. The effects of discounting notwithstanding, the figure shows that the assumption of technological learning increases investment costs in the short run, but that these costs are more than recovered later.

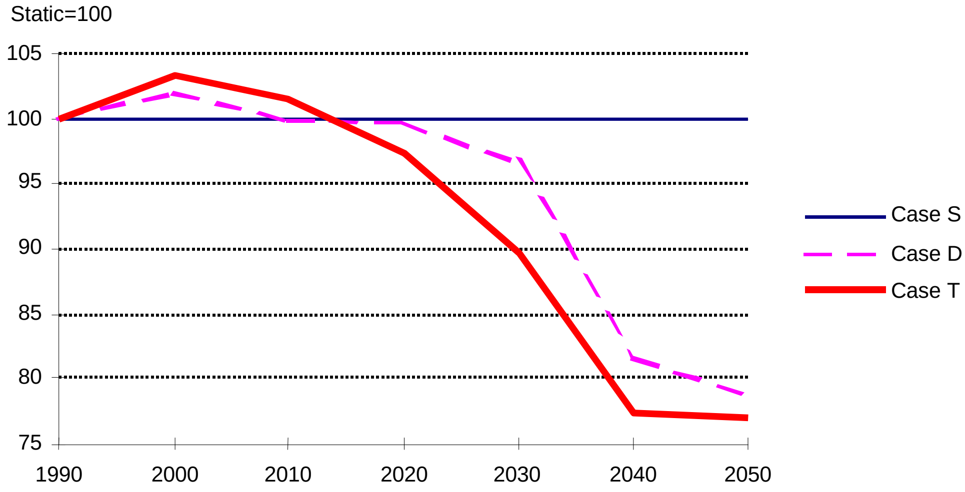


Figure 6.1 *Total annual energy system investments in an exogenous dynamic (D) and endogenised learning case (T) compared with a non-learning static case (S) (Messner and Schrattenholzer, 1998)*

*Improvement of consistency*
Including technology learning in models improves the consistency of model outcomes not only by avoiding a situation of 'learning without doing'. Another consistency improvement is on the shape of the cost reductions as illustrated in Figure 6.2.

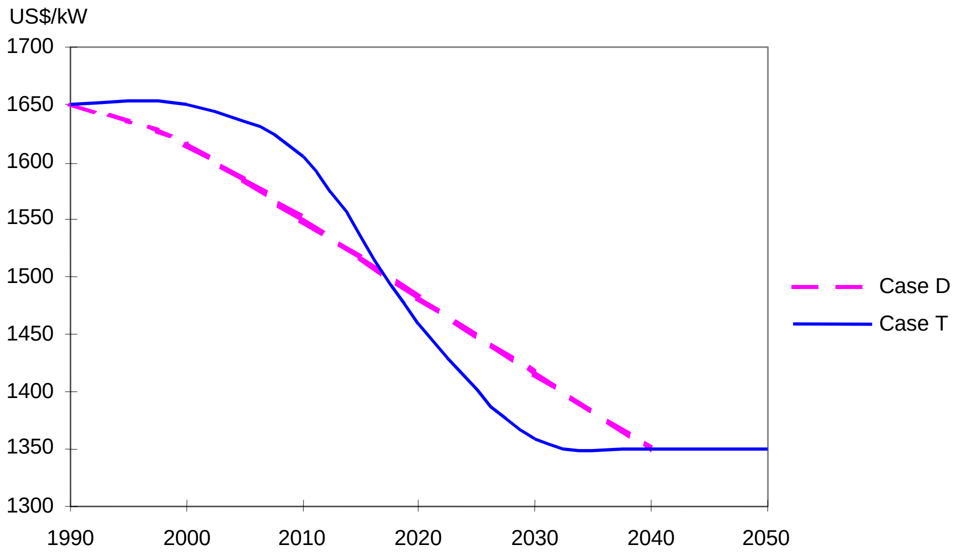


Figure 6.2 *Specific investment costs for advanced coal power plants for the exogenous dynamic (D) and endogenised learning case (T) (Messner and Schrattenholzer, 1998)*

The figure shows a typical cost reduction curve as any modeller would be likely to include it into an energy model in an attempt to describe technological progress (Case D). The curve describes linear cost decreases (equally well, it could describe exponential decreases), which is very unlike the cost decreases as described by the learning curve of Case T. This observation suggests that the formulation of learning rates in a model greatly enhances the consistency of model results no matter what learning rates are assumed. However, the relationship is often not valid at a limited regional scale, e.g. a small country.

## 6.3 Modelling energy policy measures

As illustrated in the previous section, the inclusion of technology learning in energy modelling increases the attractiveness of seemingly 'too expensive' technologies. By the same token, however, technologies with large learning potentials reduce the attractiveness of competing technologies with more limited learning potentials. Policy measures aiming to boost the learning and thereby the penetration of particular technologies will generally lead to earlier and beneficial introduction of these technologies, but the determination of an optimal mix of supported technologies could be a difficult task.

### 6.3.1 Environmental policies

The introduction of environmental taxes and emission reduction targets enables the assessment of the impact of environmental policy measures on the penetration of environmentally benign technologies. Figure 6.3 shows that a $CO_2$ tax of 25 ECU/t$CO_2$ in 2010 and 50 ECU/t$CO_2$ onwards could lead to a significant penetration of solar cells in 2000 and further on. In turn, this early penetration leads to a significant reduction of the specific investment costs of solar cells over the whole time period. Note that in the experiment reported here, solar cells already reach their assumed minimum costs in 2030. The $CO_2$ tax case leads to a 40% reduction of emissions in 2050 compared to the 1990 level. A less severe $CO_2$ reduction regime (8% reduction of 1990 emissions from 2010 onwards) does not make solar cells cost-effective.

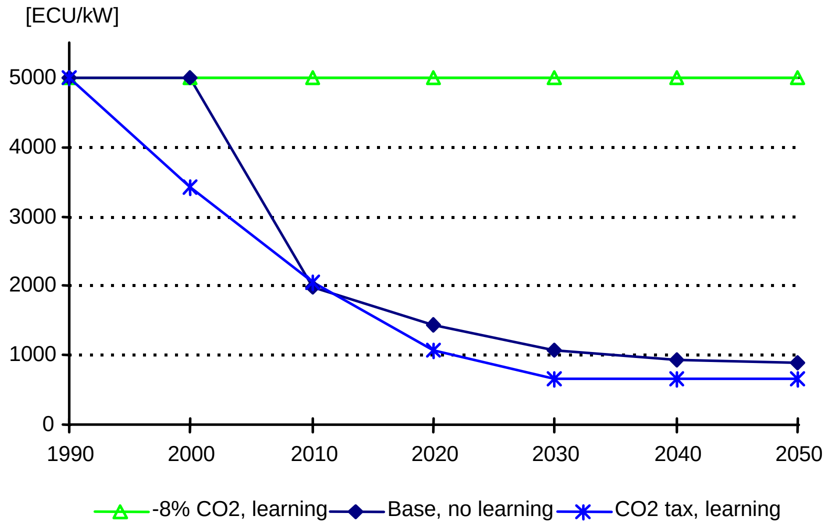


Figure 6.3 *Specific investment cost solar PV without (LP, Base no learning) and with endogenous learning (–8% CO2 reduction target and $CO_2$ tax) (Seebregts et al., 1998)*

### 6.3.2 RD&D technology stimulation measures

Technology learning parameters determine the 'learning potential' of a technology and the speed at which it can be reached (see Section 5.2). Simple extra-model calculations of 'technology maturing costs' show that the attractiveness of a 'learning' technology depends in a very sensitive and non-linear way on the learning parameters (Messner and Schrattenholzer, 1998). Such findings have been elaborated and illustrated in more detail by the PSI and ECN experiments with ERIS and MARKAL.

To illustrate the usefulness of the learning concept for RD&D policy making, ECN performed a small experiment with MARKAL, assessing three variants of stimulating the development of a fuel cell car (see Table 6.2). The variants defined are: (1) technology breakthrough through lower initial investment costs, (2) enhanced learning potential through a lower initial cumulative capacity and (3) enhanced market potential through a higher maximum cumulative capacity. In variant 2 the potential investment costs reduction of the fuel cell car is higher than in the other two variants; the latter two provide a similar potential for investment costs reduction.

These experiments show that this sensitivity of model results is particularly large for technologies which are currently not competitive and only marginally applied (but which have a large learning potential), as can be seen from the data and results displayed in Table 6.2 and Figure 6.4. This sensitivity could be regarded as an obstacle to clear guidance of RD&D decisions by model results, but at the same time, it enables the model user to quantify the benefits of successfully reaching RD&D goals. Varying the values of learning parameters of technologies, for example, could provide better insight in the impact of technology stimulation measures on the prospects of technologies, as is shown in (Seebregts et al., 1998). Lower initial investment costs could mimic a technical breakthrough as a result of dedicated RD&D efforts. A more favourable progress ratio reflects the impact of RD&D efforts speeding up the technology learning process. An exogenous increase of the value of the cumulative capacity for the first period(s) can be seen as the implementation of a demonstration programme.

Table 6.2 *Learning parameter data and learning potential of the fuel cell car in the base case and three variants (changed values of learning parameters in italic) (Seebregts et al, 1998)*

| | Base case | Variant 1 (lower $SC_0$) | Variant 2 (lower $C_{k,0}$) | Variant 3 (higher $C_{k,max}$) |
|---|---|---|---|---|
| pr | 0.82 | 0.82 | 0.82 | 0.82 |
| $SC_0$ [ECU/GJyr] | 10745 | $\Rightarrow$ *8000* | 10745 | 10745 |
| $C_{k,0}$ [PJ/yr] [4)] | 0.5 | 0.5 | $\Rightarrow$ *0.1* | 0.5 |
| $C_{k,max}$ [PJ/yr] | 1030 | 1030 | 1030 | $\Rightarrow$ *3000* |
| $SC_{min}$ [ECU/GJyr] | 1209 | 900 | 763 | 890 |
| n (number of doublings) | 11 | 11 | 13 | 13 |
| $pr^n$ [%] | 11 | 11 | 8 | 8 |
| $CO_2$ policy necessary to make it cost-effective? | yes, +++[1] | yes, +[2] | no | yes, ++[3] |

[1] $CO_2$ policy +++: an even more stringent $CO_2$ policy measure than a $CO_2$ tax of 25 ECU/t$CO_2$ in 2010 and 50 ECU/t$CO_2$ onwards, would be necessary

[2] $CO_2$ policy +: $CO_2$ reduction target -8% from 2010 on, relative to 1990 level

[3] $CO_2$ policy ++: $CO_2$ tax of 25 ECU/t$CO_2$ in 2010 and 50 ECU/t$CO_2$ onwards, equivalent to –40% in 2050 relative to 1990 level4) A more common measure is [vehicle km/yr]. The measure used here is useful energy to the wheels, which is an equivalent measure: multiplication of [vehicle km/yr], [l/km], [MJ/l] (heating value), and an overall car efficiency, results in [PJ/yr] as measure for capacity.

Figure 6.4 gives the resulting specific investment costs of these variants and two cases for comparison: the base case without endogenous learning (exogenous cost decreases linearly until 2030 and remains constant thereafter) and a stringent $CO_2$ tax case. The fuel cell car is not cost-effective with endogenous learning according to the default assumptions, even in a quite stringent $CO_2$ emission tax case (of 25 ECU/t$CO_2$ in 2010 and 50 ECU/t$CO_2$ from 2020 onwards). However, the fuel cell car is a cost-effective option in the three variants. Variant 2, providing the highest investment costs reduction potential, results in the lowest specific investment cost path, even without $CO_2$ policy. In Variant 3, wherein the maximum cumulative capacity is increased to 3000 PJ/yr, the fuel cell car becomes cost-effective only in combination with a quite extreme $CO_2$ tax. Variant 1 provides a similar investment costs reduction potential, but a limited $CO_2$ reduction regime appears to be sufficient to induce a cost-effective penetration of the fuel cell car. From the third period on, the fuel cell car is first employed and the cost decreases. Note that for this specific technology, associated $NO_x$, CO, and volatile organic compounds (VOC) emissions are not valued. Since fuel cell cars emit less of these three pollutants than conventional cars, reduction policies for these other pollutants would further boost the attractiveness of this technology.

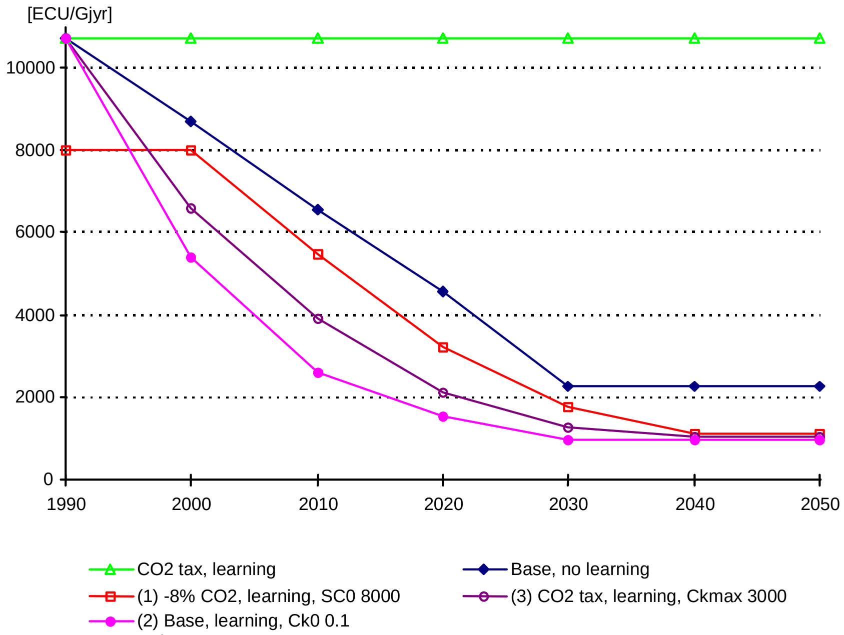


Figure 6.4 *Development of specific investment cost of the fuel cell car at different values of learning parameters (Seebregts et al, 1998)*

The effects of RD&D on the learning parameters are rather speculative and are meant here only as illustration of a possible effect. Still these model outcomes illustrate that an early and steep reduction of the initial investment cost of the fuel cell car (a technological breakthrough) can accelerate the uptake of this technology in the market. In this way the costs of additional policy measures to stimulate the penetration of the fuel cell car can be reduced. Figure 6.5 indicates that the initial investment cost could decisively affect the development of investment costs of a specific technology. The figure is also indicative for the impact of RD&D efforts (influencing values of learning parameters) that aim to speed up the market penetration of new technologies. Comparing the costs of additional RD&D efforts with the benefits on energy system costs gives a cost-benefit ratio of these policy interventions (Seebregts et al., 1998).

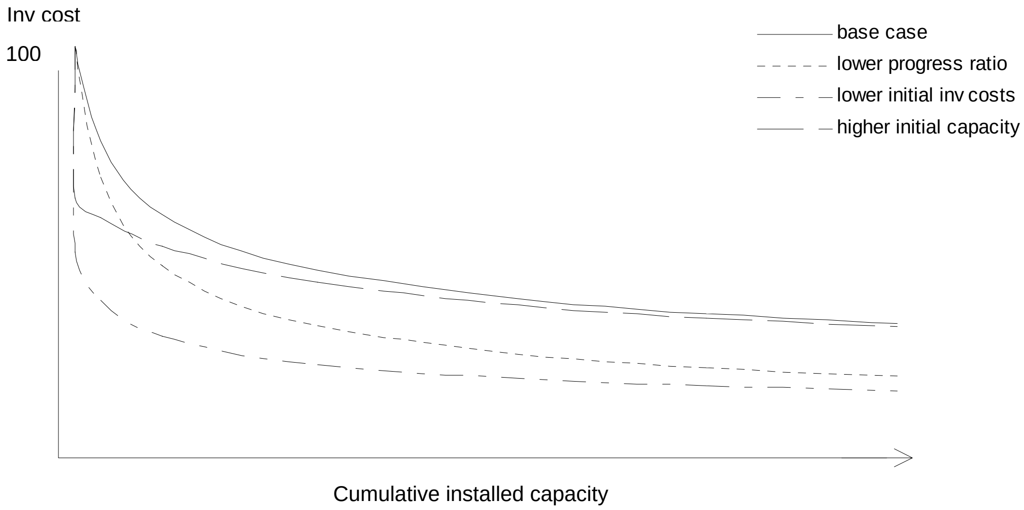


Figure 6.5 *Impact (indicative) of lower (50%) initial investment costs ($SC_0$), higher (factor 5) initial cumulative capacity $C_{k,0}$, and lower progress ratio (pr=0.75) on base case development of investment costs (pr=0.82) (Seebregts et al, 1998)*

### 6.3.3 Penetration curves for new technologies

Models that include endogenous technological learning tend to show a so-called ‘lock-in’ effect: through fast penetration of the most cost-effective technology, a drastic decline of the specific investment costs is obtained, which results in a diminishing market for other competitors. The historical development of many individual technologies shows lock-in phenomena, influenced by various market and non-market factors, whereas in the models considered here, the lock-in effect is mainly determined by costs. As other considerations than direct costs also play a role in investment decisions, some model parameters should be chosen carefully, e.g. by making use of capacity bounds and growth constraints.

The large impact of capacity growth constraints on the market penetration of power generation technologies is illustrated by Figure 6.6, which represents the global power generation mix in 2050 under a limited (5%) $CO_2$ emission reduction target from 2010 onwards at different capacity growth constraints. At a growth constraint of 15% per annum the gas fuel cell is reaching a 50% share of the generation market, mainly at the expense of gas combined cycle technologies and wind turbines. A growth constraint of 12% per annum leaves a restricted market share for the gas fuel cell, and results in a more balanced power generation mix.

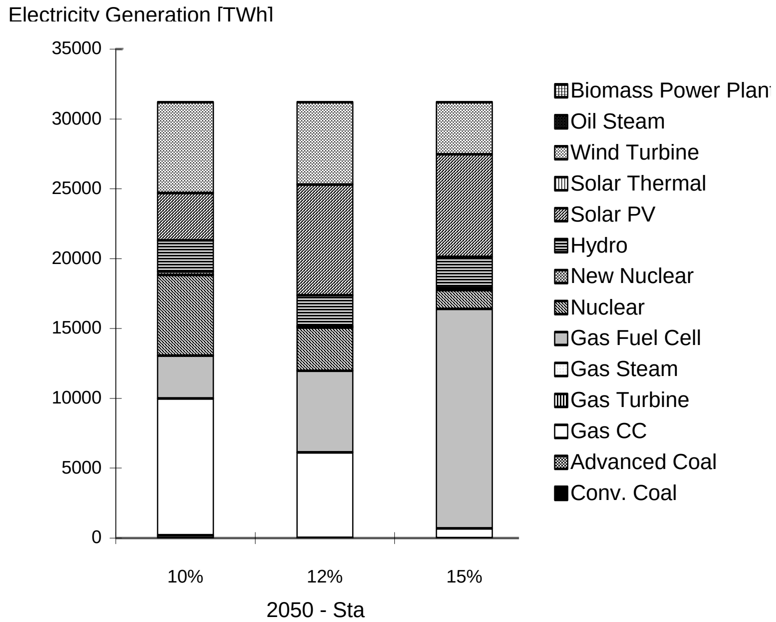


Figure 6.6 *Global power generation mix in the year 2050, 5% $CO_2$ reduction relative to1990 from 2010 onwards, at capacity growth constraints of 10, 12 and 15 % per annum (Kypreos and Barreto, 1998b)*

# 7. BENEFITS, LIMITATIONS, AND ISSUES TO SOLVE

This chapter summarises the benefits, limitations, and issues to solve associated with modelling technology learning endogenously based upon the experience with the four models as presented in the previous chapters.

## 7.1 Benefits

*Increased consistency of model results*

The main benefit and advantage of modelling technology learning endogenously is the increased consistency compared to the commonly applied exogenous cost projections. Cost development in the new formulation is fully consistent with the uptake of the technology by the market. Another important benefit is that for the optimisation, not only the decline of the specific investment costs, but also the necessary technology maturing costs are taken into account in an integrated and internally consistent way.

Moreover, the awareness of the 'learning-by-doing' mechanism on the side of the modeller tends to improve of model inputs (e.g. technology characterisation), even if the model is operated in a non-learning mode. E.g. it stresses the need for proper 'alignment' of technology dynamics between mutually dependent and competing options. In addition, model users become more alert to avoid (currently not uncommon) situations of 'learning without doing' i.e. a technology becomes cheaper and cheaper over time without being deployed until it reaches a competitive price whereupon the model starts using it.

*Guidance for RD&D and environmental policy*

The concept of technology learning provides a useful guideline for RD&D policy making prior and in addition to the quantitative results of an energy system analysis. In particular, the following policy questions can be addressed better:

- What is the possible benefit of R,D&D policy measures on the development and dissemination of specific technologies and on the energy system as a whole?
- Which technologies need additional support in order to make them cost-effective; what is the nature and extent of this support and what development targets should be aimed for?
- What is the possible impact of environmental policy (e.g. $CO_2$ emission reduction) on the technological development; as such or in combination with RD&D measures?

The model experiments reported here give insight in factors influencing the prospects of technologies and illustrate how an early reduction of the initial investment cost of new technologies can accelerate the uptake of the market, which reduces the costs of additional policy measures to enhance market uptake of these technologies. The long-term benefits of specific RD&D can be assessed and evaluated against the short-term expenditures. However, a precise cost-benefit analysis requires making daring assumptions on the effectiveness of such RD&D activities.

An important policy aspect is the possible existence of niche markets, where a competitive edge for new technologies can be obtained at limited efforts, e.g. in the case of photovoltaic cells for off-grid uses. Niche markets offer possibilities to stimulate early deployment in a particularly cost-effective way. Model databases often include a variety of applications in potential markets for technologies, largely equivalent with prospective applications in much larger markets where they are not competitive (yet). Once a concept like the introduction of 'key technologies' (see section 5.3) is implemented, assessment of spill-over effects induced by niche markets can also be considered. The potential relevance of demonstration and dissemination programs focused on suitable technology/niche market combinations can thereby be taken into account.

*Solution times remain acceptable*

The large scale, technology-rich MARKAL-Europe application shows that the increase in solution time, compared to those for the same model without endogenous learning, remain acceptable. IIASA, however, reports only results with their small scale reduced version of the global MESSAGE model and mentions difficulties in incorporating the concept in the full scale regionalised MESSAGE model (Messner, 1997). The application of the key technology concept (identified in Seebregts et al., 1998, and further elaborated in Seebregts et al., 1999) could be, apart from being a consistency mechanism, a means to cope with computational restrictions in e.g. the full scale MESSAGE model, because it helps to limit the complexity and size of the model.

## 7.2 Limitations

Although the experiments and experience with the models show much progress, it is important to be aware of limitations still existing, viz.:

- Endogenous learning is restricted to investment cost only; other technology attributes like O&M costs, efficiency, and utilisation rate remain exogenous. Although theoretically, the concept could be applied to these other attributes as well, practical reasons e.g. computational complexity would hamper such extension. Moreover, all technological change is related to a single phenomenon, ‘learning-by-doing’. Other plausible causal relationships – such as between RD&D expenditures and the progress ratio – remain without a direct influence on model results.
- The lack of reliable data describing the learning parameters and uncertainty in the additional data necessary for the new approach.
- Inter-dependent learning between clusters of technologies sharing common key components has not yet been dealt with (e.g. spill-over/cross-over effects between separately modelled technologies).
- An existing reference energy system (RES) and underlying technology characterisations may not be optimally configured to capitalise on the benefits of including technology learning.
- The decisive impact of assumed learning parameters: progress ratio, initial investment cost, initial and maximum cumulative capacity of a technology expected to learn endogenously. In particular, the cost-effectiveness of technologies with a large learning potential but currently high costs are very sensitive to these parameters, as are the benefits of policy interventions aimed at boosting these technologies. The drawback of this high sensitivity is compounded by the uncertainty of these parameters. Any set of model-based policy recommendations therefore requires a careful sensitivity analysis. Moreover, a well-targeted use of capacity bounds and expansion limits is warranted to prevent clearly unrealistic results.

## 7.3 Issues to solve

From the limitations identified above, the following issues are put forward as candidates to be solved in further research.

1. *How to deal with uncertainty with respect to learning?*

Not only the historic progress ratio itself uncertain, but it is also uncertain if it will retain the same level over the entire trajectory considered or if they might rise or decline after an initial period of learning e.g. once a certain capacity threshold is exceeded.

2. *Can we develop formal, quantitative models to link R,D&D measures directly to learning parameters, notably the progress ratio, can such models be supported by reliable input data?*

The few experiments so far indicate that the new models enable at least a qualitative assessment of the effect of RD&D policy instruments on technological development. For a more quantitative assessment, additional modelling work and corresponding reliable input data are needed. More research into the quantification of the relationship between RD&D expenditures and learning parameters is required.

3. *How to model interdependencies between technologies that share common key components?*

ECN has defined the 'key technology' concept as a possible means, in parallel to the notion of cluster of technologies, to deal with this issue. These concepts will be further elaborated on the basis of an existing rather complex RES (e.g. the MARKAL application for Western Europe) and additional model extensions. The first more detailed implementation of this concept is outlined in (Seebregts et al., 1999).

4. *Under the assumption that full-scale model applications may remain intractable due to computational reasons, how can the 'endogenous' results of reduced models be used as exogenous input into more detailed models without endogenous learning?*

Another shortcut to introducing the concept of technology learning in large models is formulate exogenous dynamic cost input data and check the consistency with the learning concept by analyzing the model results. This method has been described in (Messner and Schrattenholzer, 1998). Also (Kypreos and Barreto, 1998a) mention this type of use of small to medium scale models with endogenous learning. The real issue at stake is whether the result of small or medium scale models are sufficiently good indicators for the large scale model. A small-scale model may differ in a lot more ways from its corresponding large scale and more detailed model than only the aspect of learning. The issue can be summarised as: (1) how can reduced models be used? and (2) how much of an additional error do we introduce by this approximate method.

# 8. CONCLUSIONS AND RECOMMENDATIONS

This section summarises the main conclusions and recommendations based upon the synthesised experiences with the ERIS, MARKAL, and MESSAGE models by PSI, ECN, and IIASA.

## 8.1 Conclusions

1. All model applications are examples of successful experiments to incorporate the learning-by-doing concept in energy system models. The mathematical formulation is basically the same for all applications and has been implemented as a so-called Mixed Integer Programming (MIP) model. Although the applications of the concept were at different scales (from small to large), similar and important insights can be obtained by all of the four model applications.
2. Incorporating the learning-by-doing concept makes an important difference. A comparison between the original models with exogenous cost projections (either as constant costs over time or assuming a regular decline over time) show that the resulting technology prospects differ substantially.
3. The experiments demonstrate and quantify the benefits of investing early in emerging technologies that are not competitive at the moment of their deployment. They also show that the long-term impact of policy instruments, such as $CO_2$ taxes or emission limits and RD&D instruments, on technological development can be assessed adequately with models including technology learning. Policy measures aiming at $CO_2$ emission reduction are shown to have a clear and often decisive positive impact on the prospect of clean technologies, underlining their important role in guiding technology development towards more sustainable directions.
4. Adopting the concept of endogenous learning, several types of RD&D interventions can be addressed that aim at accelerating the market penetration of new technologies. The directions into which such interventions might lead have been illustrated in some of the experiments. However, quantitative relationships between R&D policy and learning data parameters are still unknown.

## 8.2 Recommendations for further research

To curb the most crucial limitations outlined in Section 7.2, and to address the issues to be resolved as indicated in Section 7.3, the following areas for further research are recommended. When possible, the likely TEEM partner to address the issue in the next phase of the TEEM project is indicated.

*1. The role of uncertainty*
Further investigation of the ‘two-stage progress ratio’, as implemented by PSI (Kypreos and Barreto, 1998b), collection and estimation of more reliable data and careful extrapolation into the future can contribute to solve this issue. Remaining uncertainties with respect to the parameters describing technology learning can be addressed by adopting stochastic formulations (Ybema and Kram, 1996; Ybema et al., 1998; Mattsson, 1998, Gritsevskii, 1998).

2. *The relationship between RD&D measures and learning parameters, notably the progress ratio*

Ongoing work within the TEEM project on the task 'Typology and quantification of energy technology dynamics', co-ordinated by IEPE, and possible subsequent incorporation of it in the models can contribute to solving this issue.

3. *Inter-dependency between technologies sharing key common components*

Implementation of the concept of 'key-technologies and clusters of technologies on ECN's MARKAL database for Western Europe, as outlined in (Seebregts et al., 1999), will be a first step to explore such linkages.

4. *Learning on a multi-regional global scale*

The application of learning on a multi-regional global scale could also be interesting. It would allow, for instance, the possibility of considering explicitly learning spill-over between regions, incorporating a spatial dimension to the technological learning framework. Also, the effects of the combined representation of endogenous learning (global or applied to selected regions) and other aspects of technology dynamics such as spatial and temporal patterns of technology diffusion could be addressed. Currently, endogenous technology learning is being implemented (by PSI) in the multi-region version of the MARKAL model.

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| CPLEX | Solver for LP and MIP problems (e.g. provided with the GAMS software) |
| EC | European Commission |
| ECN | Energieonderzoek Centrum Nederland (Netherlands Energy Research Foundation) |
| ERIS | Energy Research and Investment Strategy, model prototype developed in the TEEM project |
| ETSAP | Energy Technology Systems Analysis Programme, research partnership of the IEA/OECD |
| EU | European Union |
| GAMS | General Algebraic Modelling System, language in which the MARKAL and ERIS models are coded |
| GENIE | Global Energy systems model with Internalized Experience curves, global model developed at Chalmers University |
| IEA | International Energy Agency of the OECD |
| IIASA | International Institute for Applied Systems Analysis (Austria) |
| LP | Linear Programming |
| MARKAL | MARket ALLocation (energy systems model), developed and maintained within ETSAP |
| MCP | Mixed-Complementarity Programming |
| MESSAGE | Global energy systems model from IIASA |
| MIP | Mixed-Integer Programming |
| NLP | Non-Linear Programming |
| NTUA | National Technical University of Athens |
| OECD | Organisation for Economic Co-operation and Development |
| OSL | Solver for LP and MIP problems (e.g. provided with the GAMS software) |
| PSI | Paul Scherrer Institute |
| RD&D | Research, Development and Demonstration |
| RTD | Research and Technology Development |
| WEC | World Energy Council |