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ENDOGENOUS TECHNOLOGICAL LEARNING: EXPERIMENTS WITH MARKAL

Contribution to Task 2.3 of the EU-TEEM Project

A.J. Seebregts
T. Kram
G.J. Schaeffer
A. Stoffer

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Preface

This report is the deliverable of the ECN contribution to Activity 2.3 'Experience from MARKAL and MESSAGE' of the TEEM project. The ECN 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, and the Dutch Ministery of Economic Affairs (ECN project number 77126).

Abstract

This document describes the ECN contribution to Activity 2.3 'Experience from MARKAL and MESSAGE' of the TEEM project and reports on the experience gained with including endogenous technology learning in the energy optimisation model MARKAL. The objective of the TEEM project is to provide new insights for the European Union (EU) energy Research and Technology Development (RTD) strategy, focusing on policy or market induced progress of energy technologies. Activity 2.3 provides methodological recommendations, numerical results and sensitivity analyses for use in other activities of the TEEM project, based on experience with the MARKAL model with endogenous learning.

This report first describes the formulation of learning curves in MARKAL, the basic implementation of which was done by the Paul Scherrer Institute (PSI). Some conceptual issues for characterising energy technologies development and introducing technology learning in an energy system model are discussed and used to select technologies with learning from the MARKAL-Europe database. For these selected technologies learning parameters are estimated and introduced in several model cases to test the new endogenous technology learning feature of MARKAL.

The main finding is that a full-scale MARKAL model with learning is able to generate globally optimal solutions efficiently. For an optimal use of the benefits of including technology learning, some model database improvements are recommended, such as re-evaluation of the reference energy system and a well-targeted use of bounds and growth parameters. Sensitivity cases show the large impact of assumed learning parameters on model outcomes. Furthermore, model cases are analysed simulating the impact of R, D&D activities and the introduction of a CO_2 tax on technology learning and thus on the market penetration of technologies.

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1. INTRODUCTION

Technology dynamics and energy system modelling
Our understanding of the dynamics of technology in the long-term is limited. How will the current technologies have evolved? What energy technologies will become available in the next decades from now? It may well be that technologies may have emerged which have currently not or hardly been envisaged. Technology forecasting is increasingly receiving attention. Some relationships between technology driving factors, conditions required for technology development and innovation are under investigation. The notion that technologies that seem at first most promising for technical reasons are not always the ones adopted by the market is getting through. Lock-in and lock-out effects are also considered important factors. The dynamic development of relation networks between research institutes, industries, funding agencies etc. is also considered relevant. However, a grand theory to give robust forecasts of technology development is not available.

Most energy scenarios analysed with energy system models and with a relatively short time horizon assume some technology dynamics (learning). However, the trend is assumed to be exogenous 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. One of the purposes of the TEEM project (TEEM, 1997) is to investigate formulations that treat the technological learning endogenously in energy models. Recent experiments with global energy system models GENIE (Mattsson, 1997, 1998) and MESSAGE (Messner, 1997) have shown that such formulations are feasible and lead to insights not directly obtainable from the conventional models. The two models mentioned above restrict the learning mechanism to the specific investment cost and adopt a *learning or experience curve* approach: the specific investment cost decreases as a function of cumulative capacity (*learning-by-doing* mechanism). Performance indicators remain exogenous to the energy system model.

TEEM project
The objective of the TEEM project is to research and develop model-based analysis emphasising on endogenous technology evolution dynamics. The aim is to provide new insights for the European Union (EU) energy Research and Technology Development (RTD) strategy focusing on policy or market induced progress of energy technologies. The project explores the strategic issues in the perspective of climate change, by considering that energy technology dynamics can be influenced by the policies to put in place.

To meet these objectives, the TEEM projects involves major European energy modelling teams, including PRIMES (ICCS/NTUA and KUL), POLES (IEPE and ECOSIM), MARKAL (ECN, PSI, and KUL), SAFIRE (ESD) and MESSAGE (IIASA). These models follow different methodologies and rely on a variety of background experiences. Because of the difficulty of the research theme, a major objective of TEEM is to harmonise and consolidate a common methodology, among these modelling teams, to address the issue of making technology dynamics endogenous to the models.

Table 1.1 presents an overview of the way the TEEM project is structured. Details can be found in the original project programme (TEEM, 1997). ECN is mainly involved in Activity 1.4, the contribution to which has been reported in intermediate working papers, in Activity 2.3, the subject of the underlying report, and in Activity 3.4, a case study on the demand side which has to be carried out in a next phase of the project.

Table 1.1 *Workpackages (WP) and activities TEEM project*

Work package/Activity		Description
WP 1		*Development of common methodology, information and prototype model*
	1.1	Common methodology database
	1.2	Typology and quantification of energy technology dynamics
	1.3	Development of ERIS prototype model
	1.4	Development of common methodology for endogenous RTD modelling
WP 2		*Maintenance and extension of models*
	2.1	PRIMES
	2.2	POLES
	2.3	Experience from MARKAL and MESSAGE
	2.4	SAFIRE
WP 3		*Case studies and model applications*
	3.1	Application studies and update of baseline scenarios
	3.2	Centralised power generation 1995-2030
	3.3	Long term prospects: Renewables, new technologies in transports and new fuel cycles
	3.4	Demand side: efficiency, cross-cutting technologies, co-generation, small scale generation
	3.5	Evaluation of policy instruments

Activity 2.3: Experience from MARKAL

This document describes the ECN contribution to Activity 2.3 and part of Activity 1.4 of the TEEM project. The contribution comprises the reporting of experience with the energy optimisation model MARKAL (Fishbone et al., 1983; IEA-ETSAP, 1997) on including technology learning. IIASA will report separately on the MESSAGE experiences (Messner & Schrattenholzer, 1998). The objective of this activity is to prepare and synthesise methodological recommendations, numerical results and sensitivity analyses and provide them for use in other activities of the TEEM project.

Partly prior to and partly in parallel to these experiments with the MARKAL model, an other TEEM activity, the prototype model ERIS was under development. The two activities have benefited from each other's experience, e.g. as indicated by common elements in the MARKAL model and the ERIS prototype.

Contents of this report
Chapter 2 provides a general description of the MARKAL model (Section 2.1), introduces the concept of technology learning (Section 2.2), and finally, describes the database (i.e. the energy system) used for the experiments with technology learning in MARKAL (Section 2.3).

The introduction of the concept of endogenous technology learning in models like MARKAL requires a different view on the way energy technologies are characterised with respect to their development and on how learning may impact this characterisation. Chapter 3 addresses generic issues of introducing technology learning in an energy system model. In addition, Chapter 3 presents an approach for characterising energy technology development and shows the results of the approach applied to three technologies.

Inclusion of the new modelling feature also requires additional data on technology learning parameters to be estimated as input to the model. These estimates are needed for the technologies with endogenous learning. Chapter 4 describes the results of the process to select technologies with learning from the MARKAL-EUROPE database and to estimate the learning parameters for these selected technologies.

Chapter 5 sets out several cases that have been used to test the new endogenous technology learning feature of MARKAL. Chapter 6 reports the numerical results for these cases, their inter-comparison and comparisons with the conventional model formulations, with exogenous or no technology learning. Chapter 7 summarisesthe main findings from these test runs including a discussion of the benefits and of the limitations of the new approach. Finally, Chapter 8 ends with the formulation of the conclusions and recommendations.

Acknowledgement
During the course of the TEEM MARKAL activity, a close and intensive interaction has been maintained with the other MARKAL team in the project, Paul Scherrer Institute (PSI). PSI provided the basic GAMS source code that implements the concept of technology learning in MARKAL. The implementation is described separately in their report (Kypreos & Barreto, 1998c). The co-operation with Leonardo Barreto and Socrates Kypreos at PSI is highly acknowledged.

2. MARKAL MODELS AND DATABASES

This chapter presents a short description of the standard MARKAL model (Section 2.1). Next, Section 2.2 outlines the formulation to add endogenous learning to MARKAL. Finally, Section 2.3 briefly describes the MARKAL database used for the experiments with the MARKAL model with endogenous learning.

2.1 MARKAL

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) (IEA-ETSAP, 1997). The main characteristic of an optimisation model for the energy system is the concept of a predefined network of energy demands, resources and technologies interconnected by flows of energy carriers. Similar LP models are e.g. EFOM (De Kruijk, 1994; Stoffer & De Kruijk, 1997) and MESSAGE (Messner, 1997). The networks typically cover the various stages from *Primary Supply* (mining, import) of energy carriers through *Conversion and Processing* (power plants, refineries, etc.) to obtain energy products for delivery to *End-Use Devices* (boilers, cars, light bulbs, etc.) that serve to satisfy Demands for *Energy Services* broken down by (sub-)sectors and functions (residential lighting, commercial air conditioning, industrial drive power, etc.). The interconnected network of energy flows and technologies is also referred to as the reference energy system.

All pre-specified branches between sources, technologies and demands can be selected by the optimisation model. The costs and conversion efficiencies of all technologies are defined exogenously. With special functions the total costs or emissions of the energy system can be calculated. The optimal configuration of the energy system meets the specified energy demand at minimal costs. The model applies an integrated approach. This implies that synergy and competition between technologies at the supply side and the demand side of the energy system are explicitly considered.

New technologies to satisfy demands for energy services that consume less energy and/or other types of energy carriers will be indispensable to cut back future greenhouse gas emissions. Technology oriented models like MARKAL aim to identify which are the options of choice and how big their role could become over time. The system-wide (all sectors, from primary source to energy service) and dynamic (capital stock changes; load patterns) scope implies that systemic interactions like synergy, competition and load management are considered. Synergy can occur between supply and demand options, for example better prospects for electric cars if more (affordable) low emission power generation would be possible.

The *dynamic* nature implies that past decisions and future constraints are taken into account in decisions to expand or decrease capital stocks at any point in the time horizon considered in the analysis. *Structural changes* are thus allowed, but the rate at which the potential flexibilities are exploited are limited to what is both technically and economically viable. Future expectations are taken into account fully with every decision; this is called 'perfect foresight' as uncertainties play no role in these decisions.

Environmental considerations can be addressed in various ways, such as through sectoral or system-wide emission limits on an annual basis or cumulative over time. An alternative is imposing fees on emissions, e.g. reflecting carbon taxes or external costs of pollutants.

If constraints are placed on the penetration of technologies or on the total level of emissions of pollutants linked to the use of energy, the configuration of the energy system will change. In such a situation, MARKAL will again seek the configuration that has the lowest cost and that meets the constraints.

The overall optimisation *ignores stakeholders* with conflicting interests operating on markets in real life situations. Allocation of benefits and losses is thus no issue. The capability of MARKAL to *mimic 'real world'* behaviour, for instance as observed in the past, is limited. This kind of model is typically more suited to explore alternative, cost-effective strategies (for example to meet quantified emission targets) than to estimate the effectiveness of policy instruments.

2.2 MARKAL with learning curves for endogenous technological learning

2.2.1 Previous experiments with endogenous technological learning

Most energy scenarios with a relatively short time horizon assume some technological development but the technological development is assumed to be exogenous to the energy system analysis model. One of the purposes of the TEEM project is to investigate formulations that treat the technological learning endogenously in energy models. Recent experiments with the global models GENIE (Mattsson, 1997, 1998) and MESSAGE (Messner, 1997) have shown that such formulations are feasible and lead to insights not directly obtainable from the conventional LP models.

In the GENIE and MESSAGE studies just mentioned a simple relationship is assumed between the cumulative world-wide sales of an energy technology and the investment cost of the technologies. With each doubling of the cumulative sales of a technology the investment cost drops by a certain percentage. The cost reduction per doubling of sales is estimated between 0% and 30% (Neij, 1997). The cost reduction is caused by various factors but modelled as one aggregated *'learning-by-doing'* effect. In several of the studies this approach led to feed forward effects in the results of energy system models with one technology gaining the entire market while continuously becoming cheaper.

2.2.2 Approach for MARKAL

During the course of developing the ERIS prototype (TEEM Task 1.3, Capros et al., 1998), the other partner in the MARKAL team, PSI, has taken the initiative to formulate learning curves to be used in the MARKAL models. Both *Non-Linear Programming* (NLP) and *Mixed-Integer Programming* (MIP) formulations resulted (Kypreos & Barreto, 1998a; 1998b). Subsequently, ECN has incorporated and tested these two types of formulations (with slight modifications and improvements compared to the PSI versions) in the most recent 'production' version of the MARKAL model, the so-called MMARKAL version 2.2 (Decisionware, 1998).

PSI provided the basic GAMS source code that implements the concept of technology learning in MARKAL. The MIP implementation is described separately in their report (Kypreos & Barreto, 1998c).

The previously mentioned GENIE and MESSAGE models are based on MIP formulations, which proved to work quite well despite the increased computational complexity compared to the corresponding LP models without endogenous learning.

Recently, *Mixed-Complementarity Programming* (MCP) models have become attractive as alternative formulations of certain NLP models as a result of improved performance of MCP solvers. An MCP formulation of experience curves is also included in the ERIS prototype (Capros et al., 1998). ECN and PSI have decided to choose the MIP formulation of the experience curve concept to perform experiments on relatively large MARKAL models. Early experiments carried out with an NLP formulation highlighted too many disadvantages, such as: no guarantee of a globally optimal solution and problems with relatively large databases (such as the MARKAL-EUROPE database). The results of these early experiments have been reported in working papers (Kypreos & Barreto, 1998a; Seebregts, 1998a). Converting a huge energy model like MARKAL into an MCP format would go beyond the scope and resources of this project, and has therefore be deferred.

PSI has implemented learning in the multi-region version of the MARKAL model (Kypreos & Barreto, 1998c). This so-called RMARKAL version is now under development to result in the standard production version of MARKAL. ECN used the PSI MIP implementation for RMARKAL as basis for the implementation in MMARKAL (version 2.2). Only a few number of modifications and improvements were needed to have it successfully working in MMARKAL. The PSI MIP formulation embedded in the ERIS prototype (Kypreos & Barreto, 1998b,1998d) is basically identical to the MARKAL formulations. The main differences in the ECN version of the MIP formulation for experience curves in MARKAL are summarised in Table 2.3.

Table 2.3 *Main differences of ECN MIP implementation for MARKAL compared to PSI version*

MMARKAL 2.2 in stead of RMARKAL 3.0 (Note: successful test have already been tested with MMARKAL 2.3, available since November 1998)
Segmentation of cumulative cost curve.
Add, if desired, multiple solves within one MARKAL run: - LP solve (without learning) with constant investment costs prior to MIP, - iterative MIP solves with adjusted values for the maximum cumulative capacity parameter.
Explicitly make investment zero in time periods before the technologies is available.
Restart a MARKAL run with a previously determined MIP solution (perturbation run).

2.2.3 Mathematical formulation of learning curves in MARKAL

For completeness, this section presents the mathematical description of the MIP formulation for learning curves in MARKAL (adopted ans slightly adapted with kind permission from (Barreto, 1998b) and (Kypreos & Barreto, 1998b, 1998c)). It should be noted that the endogenous technological development is restricted to the investment costs only. As indicated in (Kypreos & Barreto, 1998b), the fixed operation & maintenance (O&M) costs can be treated in a similar fashion. Changes in other parameters, e.g. efficiency and availability factors, are still treated exogenously. Given the novelty of modelling technology endogenously, it was decided to first gain experience with including dynamics in costs, as a first, important leap forwards. It is expected that learning on other aspects or other model improvements can be addressed in the forthcoming TEEM case studies in WP 3.

The formulation below corresponds to the one described by Mattsson (1997).

The learning curve

A *learning, or experience curve*, describes the specific cost as a function of the cumulative capacity for a given technology. It reflects the fact that some 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* (Grübler, 1998). 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:

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

Where:

SC: Specific cost

C: Cumulative capacity

b: Learning index (constant)

a: Specific cost of the first unit (constant)

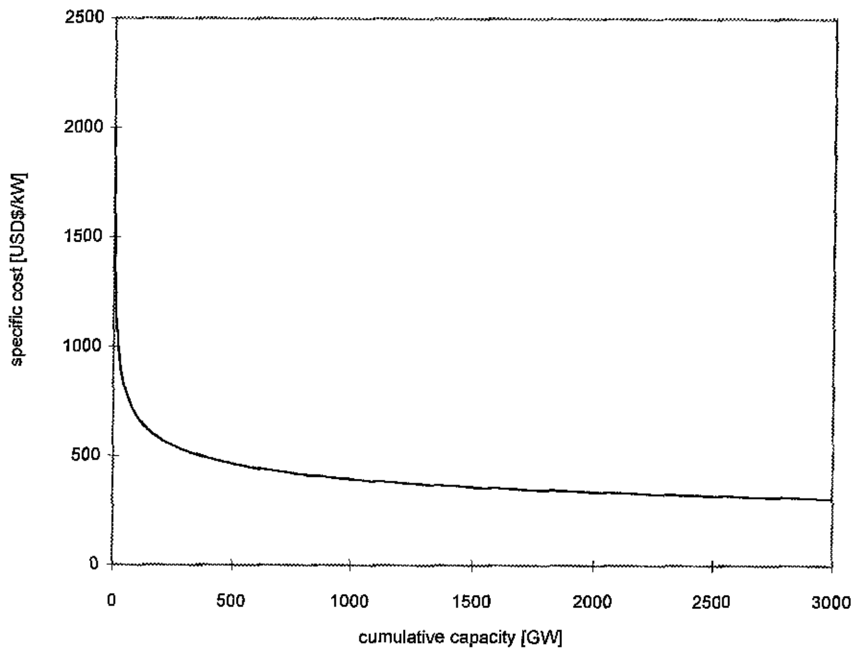


Figure 2.1 *Example of a learning curve*

The *learning index* b can be derived from the *progress ratio.* The progress ratio (*pr*) is defined as the rate at which the cost declines each time the cumulative production doubles. It can be expressed as a function of the learning index as:

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

This parameter constitutes one of the key assumptions of the problem because it defines the speed of learning for the technology.

At least one point of the curve is required to estimate the coefficient a. Normally, the initial point (C_0, SC_0) is specified. Up to this point, C_0 units have been installed and the unitary cost is at the SC_0 level. Then, this point represents the cumulative experience gained previously. However, for technologies still in the pre-commercial stage, this information may not be available and this sensitive starting point has to be carefully defined.

Definition of the cumulative cost curve

The total cumulative cost (*TC*) as a function of the cumulative capacity will correspond to the integral of the specific cost expression:

$$TC = \int_0^C aC^{-b} \times dC$$

That becomes:

$$TC = \frac{a}{-b+1} C^{-b+1}$$

This is a non-convex function. The MIP approach will provide a procedure to implement the piecewise linear interpolation of the cumulative cost curve.

Definition of cumulative capacity

The cumulative capacity of a given technology k for the period t is expressed as:

$$C_{k,t} = C_{k,0} + \sum_{\tau=1}^{t} INV_{k,\tau}$$

$k \in \{1, \ldots\ldots K\}$
$t \in \{1, \ldots\ldots T\}$

Where the parameter $C_{k,0}$ is the initial cumulative capacity that defines the starting point on the experience curve for the technology k (a corresponding cumulative cost $TC_{k,0}$ is also defined). The variable $INV_{k,t}$ represents the investments made on this technology in a particular period t.

Maximum cumulative capacity and cumulative cost

In order to specify the curve to be interpolated, a maximum amount of cumulative capacity $C_{k,max}$ is defined. The corresponding maximum cumulative cost is given by:

$$TC_{k,\max} = \frac{a}{-b+1}\left[C_{k,\max}{}^{-b+1}\right]$$

Declaration of number of segments

The number of segments N for the cumulative cost curve is specified. As N determines the number of integer variables per technology and period, it has to be a trade-off between the precision required for the approximation and the solution time.

Definition of the kink points for cumulative costs and capacities

Using the initial and final points of the curve and according to the number of segments previously defined, the breakpoints are computed. In its most simplest form, the segments are defined as follows:

For i=0,...N-1

$$TC_{i,k} = TC_{0,k} + i \cdot \frac{\left(TC_{k,\max} - TC_{0,k}\right)}{N}$$

And the corresponding cumulative capacities:

$$C_{i,k} = \left(\frac{(1-b)}{a} \left(TC_{i,k} \right) \right)^{\frac{1}{1-b}}$$

Other segmentations may, of course, be used. E.g., PSI used:

$$TC_{i,k} = TC_{0,k} + \frac{\frac{1}{2^{N-i}} \left(TC_{k,\max} - TC_{0,k} \right)}{\sum_{i=0}^{N-1} \frac{1}{2^{N-i}}}$$

This type of segmentation is presented in Figure 2.2. ECN used also a segmentation based on a logarithmic division. 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 curve.

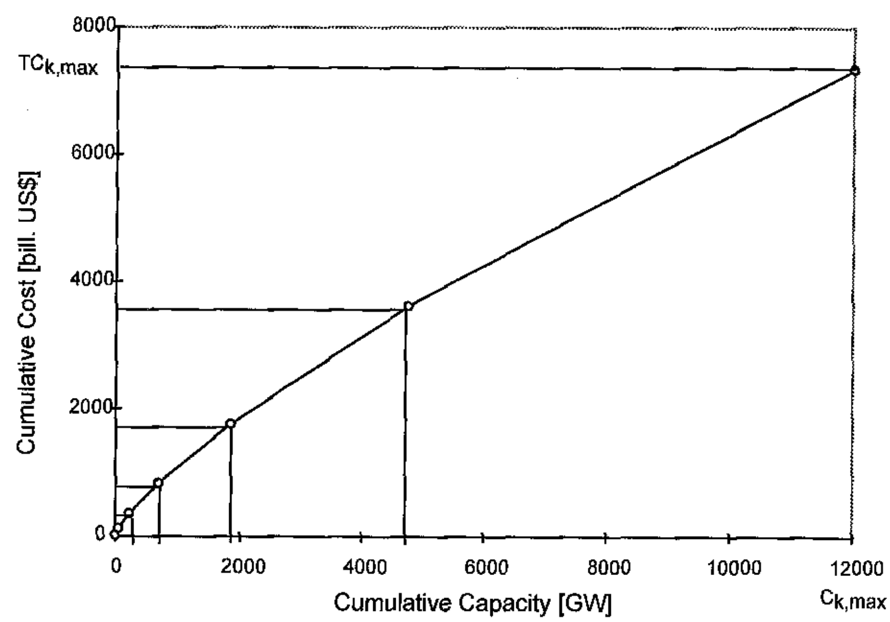


Figure 2.2 *Piecewise approximation of the cumulative cost curve*

Interpolation of cumulative capacity

The cumulative capacity is expressed as a summation of continuous lambda variables. There will be as many lambda variables as segments have been defined:

$$C_{k,t} = \sum_{i=1}^{N} \lambda_{k,i,t}$$

Interpolation of cumulative cost

The cumulative cost is expressed as a linear combination in terms of the continuous lambda and binary delta variables:

$$TC_{k,t} = \sum_{i=1}^{N} \alpha_{i,k} \times \delta_{k,i,t} + \beta_{i,k} \times \lambda_{k,i,t}$$

$$\delta_{k,i,t} \in \{0,1\}$$

With:

$$\beta_{i,k} = \frac{TC_{i,k} - TC_{i-1,k}}{C_{i,k} - C_{i-1,k}}$$

$$\alpha_{i,k} = TC_{i-1,k} - \beta_{i,k} C_{i-1,k}$$

The coefficient $\beta_{i,k}$ represents the slope of each one of the segments. The coefficient $\alpha_{i,t}$ is the corresponding TC-axis intercept of each linear segment. Only one delta variable will be non-zero at the same time, indicating the active linear segment.

In fact, the specific cost (SC) corresponds to the slope of every linear segment of the cumulative cost curve, that is to the coefficient $\beta_{i,k}$. Although the piecewise representation is done directly on the cumulative cost curve, the examination of the resulting stepwise curve for the specific cost provides an idea of its accuracy (see Figure 2.3).

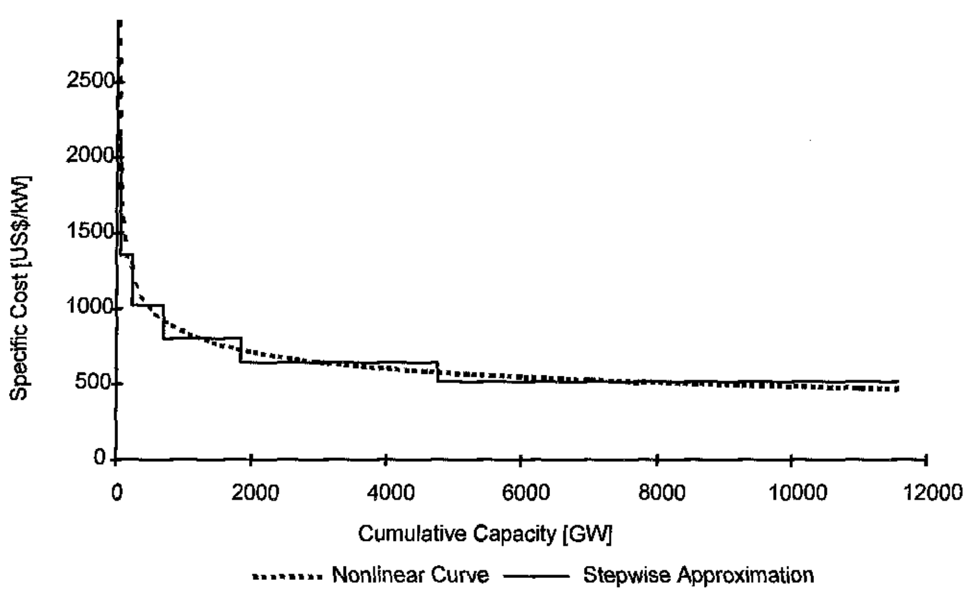


Figure 2.3 *Stepwise approximation of the specific cost curve*

Definition of the investment cost
The investment cost $IC_{k,t}$ associated to the investments in technologies following the learning curve can be computed as:

$$IC_{k,t} = TC_{k,t} - TC_{k,t-1}$$

The corresponding discounted investment costs are included in the objective function of MARKAL.

Logical constraints in terms of lambda and delta variables
The logical conditions regarding the control of the active segment of the cumulative curve are defined using the help of binary variables delta:

$$\lambda_{k,i,t} \geq C_{i,k} \times \delta_{k,i,t}$$
$$\lambda_{k,i,t} \leq C_{i+1,k} \times \delta_{k,i,t}$$

This group of constraints basically relates the continuous variable $\lambda_{k,i,t}$ to a corresponding binary variable $\delta_{k,i,t}$, ensuring that lambda remains between the two corresponding successive cumulative capacity points ($C_{i,k}$ and $C_{i+1,k}$).

Sum of delta variables to one
In order to ensure that only one binary variable can be active every period, for every technology k and every time period t, force the sum of delta binary variables to one:

$$\sum_{i=1}^{N} \delta_{k,i,t} = 1$$

Definition of additional 'unnecessary' constraints
Using the fact that experience must grow or at least remain at the same level, some additional constraints may be added to the basic formulation. These constraints provide a relation between the binary indicator variables $\delta_{k,i,t}$ across periods, according to the sequential order that must be followed, and help to reduce the solution time.

For t=1,......T
k=1, ...K
i=1,......N

$$\sum_{P=1}^{i} \delta_{k,P,t} \geq \sum_{P=1}^{i} \delta_{k,P,t+1}$$
$$\sum_{P=i}^{N} \delta_{k,P,t} \leq \sum_{P=i}^{N} \delta_{k,P,t+1}$$

2.3 MARKAL-EUROPE database

The model database used for this study is based on *MARKAL-EUROPE* 1.0 (Ybema et al., 1997; Lako & Ybema, 1997). This model has been defined for Western Europe (the 15 European Union member countries and Norway, Switzerland and Iceland). The time span covers the period from 1990 to 2070 (although results are only reported until the year 2050).

This MARKAL database is especially suited for this study because:
- It represents a large market (15 EU-countries), which allows the concept of technology learning to be applied for.
- It includes a large amount of technologies and a sufficiently long term time horizon, which favours a comprehensive analysis of the impact of endogenised technology learning on the cost effectivity of technologies. Furthermore, it provides relevant experience on the computational performance of future MARKAL model versions.
- Its results based upon the regular LP version of MARKAL are well reported, which favours a comprehensive comparison of the model results of the LP and the MIP version of the MARKAL model.

MARKAL-EUROPE takes the overall overview of Western Europe as the perspective for model calculations. This assumes a situation that only one actor decides what the structure of the energy system will look like. The model assumes free competition of the technologies fully based on the cost-effectiveness of the technologies. With its dynamic nature, MARKAL performs an optimisation of the energy system for the full period 1990-2070 in one set of iterations. This implies that perfect foresight applies.

Western Europe does not have a homogeneous energy system; there are large differences between the kinds of end use and the primary energy mixes of the various countries. Up to a certain level, regional detail has been included in the model definition. Space heating and hot water demand has been considered for three regions North, Middle and South. Renewable energy potentials have been considered in tranches depending on the site-specific energy production. The approach reflects the view that differences between countries will become less important over time with the liberalisation of the energy markets in Western Europe, the gradual integration of the economy and policy making within Western Europe and globalisation of energy technology markets.

The MARKAL-EUROPE database is very detailed in the modelling of the end-use sectors. An overview of the kinds of energy end-uses considered in MARKAL-EUROPE 1.0 is given in Table 2.1.

The currently existing stock of capital and the associated energy use is considered as the starting point for the development of the energy system. The model has been calibrated to reflect the historic energy balances in the year 1990. It has been assumed that electricity can be freely traded in Western Europe from the year 2010 onwards.

Maximum penetration of technologies can be regulated in the model by imposing maximum bounds on total capacities and/or maximum bounds on new capacity. Examples of technologies that have bounds in MARKAL-EUROPE 1.0 are wind turbines, PV systems, geothermal energy and district heat. The bounds can be justified on the base of different real constraints: public planning constraints (e.g. wind turbines), limited (growth of) manufacturing capacity (e.g. PV systems), physical constraints (geothermal resources), heat demand in areas with high heat load (district heating), etc.

Based on MARKAL-EUROPE 1.0, ECN has recently developed two other European MARKAL databases: the MARKAL-MATTER database and the MARKAL-EUROPE 2.0 database.

The MARKAL-MATTER (MATerials Technologies for greenhouse gas Emission Reduction) database is an extended version of the MARKAL-EUROPE 1.0 database. The energy system model has been extended with a new biomass module and the modelling of the transportation sector has been adjusted. The original final demand for a fixed quantity of certain materials has been replaced. A new module represents the life cycle from materials production, product manufacturing, product use and waste handling. The final demand is now set for products instead of materials. More details on the MATTER database can be found in (Gielen et al., 1998; Gielen, 1997; 1998a, b, c; Gielen & Kram, 1998).

The MARKAL-EUROPE 2.0 database is a recent update of the MARKAL-EUROPE 1.0 database, aimed at analyzing the prospects of fusion power in Western Europe, as part of the EU-SERF (Socio-Economic Research on Fusion energy) programme. The time horizon has been extended to 2100. In addition, technology data of the power generation sector has been updated. More details can be found in (Lako & Seebregts, 1998), (Lako et al., 1998a), and (Lako et al., 1998b).

Table 2.1 *Overview of the useful energy demand categories in the MARKAL-EUROPE model*

Industry	Households	Transport	Commerce
Aluminium production	Space heating single	Passenger car	- Space heating
Bricks production	houses:	Van	- North Europe
Chlorine production	- North Europe	Truck	- Middle Europe/large
Steel production	- Middle Europe/old	Bus	- Middle Europe/small
Polyolefine production	- Middle Europe/new	Rail Transport	- South Europe
Ammonia production	- South Europe	Water Transport	Other commercial
Olefine production	Space heating	Inland	electricity demand
Styrene production	apartments:	Air Transport	
Cement clinker	- North Europe	Bunkers	
production	- Middle Europe		
Paper production	- South Europe		
Non Energy Use:	Water heating:		
Lubricants+Bitumen	- North Europe		
Other industry:	- Middle Europe		
- large high temp. heat	- South Europe		
- small high temp. heat	Dishwashers		
- large low temp. steam	Food preparation		
- small low temp. Steam	Lighting		
- electricity	Refrigerators/freezers		
	Tumble dryers		
	Washing machines		
	Other electric appliances		

3. GENERIC ISSUES AND ENERGY TECHNOLOGY CHARACTERISATION

3.1 Introduction

Dealing with endogenous learning in energy models invokes several questions that relate to the dynamics of technological development. To tackle these questions an internal paper was prepared by one of the team members. This internal paper has been based on results from an extensive study on the dynamics of fuel cell technology (Schaeffer, G.J., 1998). In this chapter several issues from this internal paper will be discussed (section 3.2). In section 3.3 an approach to energy technology characterisation with respect to learning as put forward in the internal paper will be treated. This is followed by an application of this approach to three energy technologies in section 3.4. The chapter will be concluded with some conclusions in section 3.5.

3.2 Generic issues

Incorporating learning in energy models is a learning experience in itself. In this section some of the practical and conceptual issues the ECN-team has encountered in this learning process, will be reviewed.

3.2.1 Endogenous alignment of technology characterisation

In models with exogenous technology development many different technologies are defined in the models' technology databases. The parameters characterising these technologies are 'aligned' (made consistent with each other) exogenously by the modellers. For instance, if a certain assumption is made on the costs of a combined cycle for central electricity production (in a certain year), then the modellers will choose for costs of a combined cycle for combined heat and power applications that will not differ too much from this assumption. This process of exogenous alignment of characterisation parameters cannot be performed in a model with endogenous learning (with the exception of the starting values). This could mean that in the model the same technology (e.g. PV) can learn in one market (e.g. in southern Europe) and consequently become cheaper by the experience effect, while the same technology in other markets (e.g. in northern Europe) will not learn and keep its high initial price. This will make the database inconsistent. Therefore, in one way or another, a mechanism should be found that replaces the exogenous alignment practices in the traditional models by an endogenous mechanism.

3.2.2 Key technologies

An approach that could be taken to achieve endogenous alignment of technology characteristics, is to define key technologies. Key technologies are technologies that are a component in many other technologies in the database. 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. A list of these key technologies can be found in Chapter 4. In the further development of endogenous learning models the possibilities how learning effects can be transferred to key technologies should be explored. If this can be done in an appropriate way, the application field of the model can be broadened significantly, for instance to investigate how stimulation in one market can influence the chances of a technology in another market.

3.2.3 Appropriate level of aggregation or detail

The appropriate level of aggregation or detail of a technology characterisation in models depends on the purpose of the use of the 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 performances will be reached, but only that these improvements can be achieved. The more detailed forecasts are, the higher the risk that they will not come true. A good example of a process of technological development showing regularities at a higher aggregation level comes from the micro-processor industry. Within this industry 'Moore's Law' (see e.g. Gibbs, 1997), which states that the number of integrated circuits on a chip will double every 18 months, holds very well since the late 1950's. The 'law' however, does not say what technologies will be needed to reach these improvements in performance.

In models with exogenous technology development the assessment of future costs of technologies is often based on expert judgements, which in their turn are derived from detailed analyses of a technology's components and the improvements that are perceived as possible. The result of this 'component-approach' is that technologies often are defined at a very detailed level. For instance certain types of fuel cells are defined (e.g. phosphoric acid fuel cells (PAFC)) for certain kinds of applications (e.g. decentral combined heat and power (CHP)). An analysis of the history of fuel cell shows that dominant insights about the proper 'type-application' combinations have changed several times. In the middle of the 1980's for instance fuel cell buses were expected to be driven by PAFC's. During the 1990's the solid polymer fuel cell (SPFC) has taken over this prospective application. For a modeler of energy systems, however, in many cases there is no reason to make a choice between the two alternatives.

3.2.4 Learning on multiple parameters

Most efforts on incorporating technological change in energy models during the TEEM-project (and before) have focused on investment costs. This is one of the most important parameters that characterise the technologies in the available databases. However, it is well known that also other characteristics of technologies change, such as operation and maintenance (O&M) costs and performance (e.g. electrical efficiency) are relevant factors to the final costs of energy. One possibility to deal with this is to correct the estimated investments cost for the improvement of performances (see e.g. Criqui, 1998). This approach however has several disadvantages. In the first place several assumptions have to made about interest rates and depreciation periods. Secondly, it disturbs the outcomes of sensitivity analyses with interest rates, or differences in fuel prices. Another approach is to model learning mechanisms for these parameters separately. Typical performance improvement trajectories follow an S-shaped curve, in time or in relation to cumulative production (see e.g. Cohendet et al., 1993).

3.2.5 Balancing the choices

Introducing endogenous learning in energy models induces more severe requirements for calculation time and memory space. At the current state of the hard- and software performance, only a limited number of technologies can be chosen to be subject to endogenous learning. In Chapter 4 a few criteria are put forward to select those technologies for which endogenous learning is most appropriate. If a certain technology is selected to be treated in a model with endogenous learning, then special attention should be given to the characterisations of those technologies that are in direct competition with this technology, to avoid unrealistic competition between a learning and a non-learning technology. This means for instance that if fuel cells for power production are chosen to be a learning technology, also gas combined cycles should be treated in the same way.

3.3 Characterising technological developments

3.3.1 Four basic questions

The progress ratio of a technology is one of the most important parameters in models with endogenous technological learning. The question is how to estimate a plausible progress ratio for different technologies. A first-round answer is to base the progress ratio that is expected in the future on historical data, if available. The same can be done for learning trends in other model parameters, such as efficiencies. But the appearance of a certain progress ratio in the past does not guarantee that the same progress ratio will prevail in the future. The conditions for this to happen have first to be investigated. Several of these conditions can be distinguished:

1. It must be plausible that the technology development in question will continue at all. In the past many energy technologies have been proposed and included in energy model technology databases, that later appeared to choke in their development. Ex-

amples are the Magneto-Hydro-Dynamic (MHD-) technology or 'hybride-hydride-cars' (see e.g. Okken et al, 1993).
2. A second condition is that the focus of a technology development (the technology paradigm) will remain the same. For instance if this will be the case for the fuel efficiency of person cars in terms of liters per vehicle-kilometer, then the historical trend (no improvement during the last 10 to 15 years) will only be broken if the focus in the development departments of the automobile industry will shift (e.g. enforced by policy measures) from comfort and safety to fuel efficiency by new propulsion technologies and lighter materials.
3. A third condition is that the overall constitution of the context in which the developments take place does not substantially change. It can be imagined that different progress ratios are achieved for a technological development that is mainly R&D driven, than for technologies that are mainly market driven. After all, progress ratios are not more than correlation factors between cumulative production and costs, and this correlation can change if the R&D intensity changes.

The considerations mentioned above mean that in order to characterise technological developments and to assess the value of their progress ratios, four basic questions should be answered:
1. Is there a historical trend from which a historical progress ratio can be determined?
2. Is it plausible that the technology will continue to be developed at all?
3. Will the direction of the development remain the same or will its course be altered?
4. Is it plausible that the progress ratio observed will stay the same, or will it decrease/increase?

The first question can be answered by collecting appropriate data. If the first question cannot be answered positively, the assessment of proper progress ratios becomes a lot more difficult. In that case a comparison could be made with existing technologies. However, in most cases technologies included in energy technology databases have a substantial long development history (see for instance the list of key technologies in Chapter 4).

The remaining three questions are related to the degree of stability of a technological development. In the following sub-section some notions and ways to assess the degree of stability will be clarified.

3.3.2 Stability in technological developments

The application of experience curves assumes that the technology analysed by this method will undergo a steady and stable technological development in the future. The question is, how sure can we be that this will be the case? In other words, how can we assess the degree of stability of a technological development? A distinction can be made between two kinds of stability: stability with regard to the links of a technology with the relevant external environment (*system stability*) and stability with regard to the internal relations and structures of a technology (*convergent stability*).

To make the distinction between these two kinds of stability a little more clear, Figure 3.1 might be helpful. System stability occurs when neither insiders (*appeal*), nor outsiders (*agression*) claim that the outcomes of the technological development under consideration are to be disliked. In that case no transformation of what Van de Poel (1998) calls the *technological regime* can be expected.

Convergent stability occurs when the internal dynamics of the interaction system does not cause changes in the outcomes that are different from what could be expected by extrapolating the trends. In other words convergent stability is stability within a technological regime.

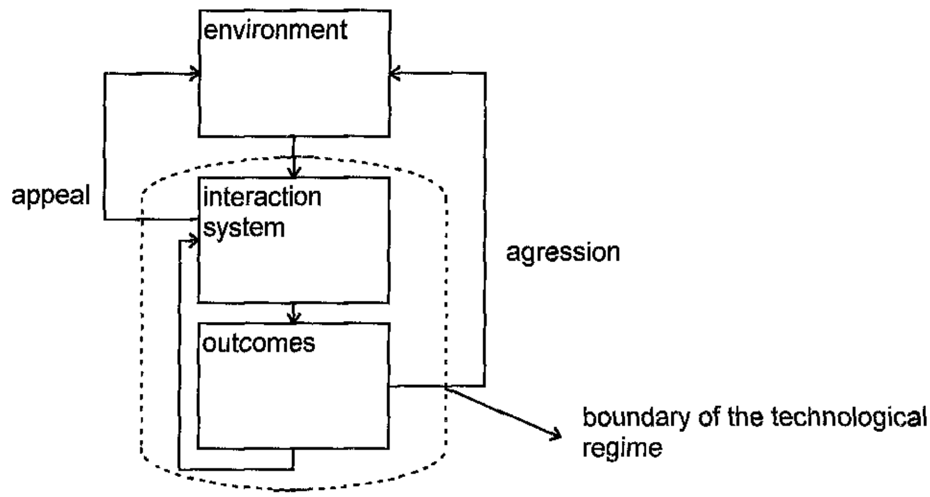


Figure 3.1 *Technology as a system of innovation and its environment*

Following Figure 3.1 three sources of transformation of technological regimes caused by links of the regime with the environment can be distinguished:
- change because the *environment* changes by its own dynamics (*external change*),
- change because outsiders consider the outcomes of the technological development as undesirable (*aggression*) leading them to action to intervene,
- change because insiders consider the outcomes of the technological development as undesirable (*appeal*), leading them to ask outsiders to intervene.

3.3.3 Assessing system stability

A method to assess the system stability of a technology is to systematically investigate the relevant aspects of the environment that legitimate and justify the activities sustaining the development and to assess wether the outcomes of this process might form a reason for insiders or outsiders to contest the desirability of the development as a whole. This can be done by asking systematically the following questions:
1. What are the relevant macro-agenda issues in the environment that are used as a legitimation or justification to sustain the ongoing activities? Are there reasons to believe that the importance of these issues will change in the future?
2. For which reasons would the outcomes of the technological development under consideration form a possible source of concern by outsiders?

3. For which reasons would the outcomes of the technological development under consideration form a possible source of concern by insiders?

These questions can be asked in different ways and to different audiences. These questions could be included in standard expert opinion methods, but also be investigated by analyses of texts commenting on a technological development produced by insiders or outsiders.

An example: Suppose that a group of experts is asked to answer the questions just mentioned for three technologies, i.e. wind turbines, fuel cells and CO_2 removal technologies. Possible answers to these questions for these three technologies are given in Table 3.1.

Table 3.1 *Possible comparison of system stability for three energy technologies*

Technology	Legitimating aspects in the environment	(Possible) reasons for appeal	(Possible) reasons for aggression
Wind turbines	finite resources global warming local and regional environmental problems	lack of knowledge of off-shore technology among turbine manufacturers	distortion of landscape, sea-sight and nature
CO_2 removal and disposal	global warming	lack of knowledge of how CO_2 behaves in oceans among CO_2 removal specialists	costs and energy use
Fuel cells	finite resources global warming local and regional environmental problems	lack of knowledge on user's requirements among developers of fuel cells	possible toxicity of materials or fuels for fuel cells.

The *system stability* of each of the three technologies can be compared to each other. From Table 3.1 it can be seen that the only macro-agenda issue that is addressed by CO_2 removal technologies, is the issue of global warming, whereas the other two technologies address other issues as well. In this sense CO_2 removal technologies have less system stability than the other two technologies. However, global warming currently is a very important issue on the global societal agenda, and the link between CO_2 removal technologies and the global warming problem is at least as strong as the link between the global warming problem and the other two technologies. In other words, scores on the importance of the issues that are claimed to be addressed by the technology, as well as the strength of the links between the technology and the issue addressed should be constructed to assess the current system stability of a technology. Table 3.2 is an example of how this could be done. The first column gives an example how, on a scale from 1 to 3 the importance of each of the macro-agenda issues could be scored, e.g. by a group of experts. In the following columns the strength of the relation between the technology and the issue is estimated on a scale from +3 to -3 (CO_2 removal technologies could be given a negative relation with the problem of the world energy supply, because the removal of CO_2 reduces the efficiency of the power plant). In the last row the total score is calculated for each technology.

Table 3.2 *Possible system stability scores for three energy technologies*

Issues	Importance of the issue	Link with fuel cells	Fuel cells issue stability score	Link with wind turbines	Wind turbines issue stability score	Link with CO_2 removal technologies	CO_2 removal technologies issue stability score
Finite resources	1	1	1	2	2	-1	-1
Global warming	3	1	3	2	6	3	9
Local/regional environmental problems	2	3	6	2	4	0	0
Total stability score			12		12		8

The scores in Table 3.2 give an indication of the relative system stabilities of the three different technologies with regard to the current prevailing macro-agenda issues and their current importance. It shows that although a technological development is only related positively to one macro-agenda issue instead of to three, the current system stability does not need to be only one third of the other two technologies, if the relevant macro-agenda issue is seen as more relevant than the other issues. For the future it is important to assess how the importance of the different macro-agenda issues will vary. This issue of dealing with uncertainty is treated by the hedging approach with regard to CO_2 reduction levels. System stability characterisation exercises such as shown in Table 3.2 help to define the sensitivity between CO_2 reduction uncertainty and technological learning. If the external legitimisation of a technology is only dependent on the global warming problem, the activities to develop and improve this technology will depend only of the value of this macro-agenda issue. Activities for the development of other technologies will be affected less if the macro-agenda issue of global warming will loose its importance.

3.3.4 Assessment of convergent stability

Convergent stability refers to the seeming autonomy of technological developments. Many in-depth sociological studies of innovation processes have shown that there is no such thing as an autonomously developing technology, but several mechanisms can be distinguished that make it hard to change the course of a development. These mechanisms can be related to the interplay of three elements of technological development, i.e. actors, artefacts and agenda (Figure 3.2) (Van Lente, 1993). In this interplay of mechanisms all three corners of the triangle play their role, but in some cases one corner is more dominant than the other.

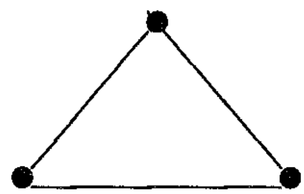


Figure 3.2 *The triangle of technological developments*

Nuclear fusion for instance owes its continuing development, in spite of changing environmental forces, for a large part to what can be called 'materialised stability' (artefact-related stability). The fact that in the past at a few places in the world very large and costly research facilities have been built, makes it in the first place difficult to stop such research at all and in the second place makes it difficult to change the orientation of the development.

Fuel cells is an example of a technology for which a complex kind of actor-dynamics has secured its continous progress and development from the late 1940's till today (actor-related stability). At a given moment in time there are many research activities going on that focus on the development of a specific technology. These projects produce a constant flood of 'products', such as scientific articles, conference presentations, contributions to articles aimed at the general public in magazines and newspapers, demonstration plants, feasibility studies, and so on. These products embody and contribute to the general 'promise of the fuel cell', on the basis of which new actors start to undertake development activities. Once such a project or program has started, actors start to commit themselves enthusiastically to the path chosen. Even in cases in which the original projects, on which the promise to start new activies was based, fails to deliver the promise and is discontinued, the new projects are not stopped, but instead proceeded with even more enthusiasm. If results are not as promised/expected, actors appear to possess a whole gamma of means to protect the ongoing activities. Targets can be reformulated, deadlines postponed, references can be made to similar problems in other on-going activities, outcomes of research activities can be interpreted in different ways and considerations of international competition can be brought to the foreground. Not in all cases actors succeed in protecting their activities sufficiently and some activities might stop. However, during the life time of a project, the promise of the technology under development has been broadcasted many times, inducing new activities elsewhere.

Agenda-related stability is related to which direction the future of a technology is going. Concepts as technological paradigm and technological guidepost fall within this category. A good example of a technological paradigm change that has accurately been anticipated by actors in the relevant technological community is the 'turbo-jet revolution' in aircraft technology. Although not many actors were involved in dealing with turbo-jets, and not many turbo-jets existed yet, the aeronautical community of engineers agreed that the propeller technology could only get the speed of an airplane to a certain maximum limit. To achieve higher speeds another technology (the turbo-jet) had to be developed, which happened. Another example, Moore's Law in the semi-conductor industry, has been mentioned earlier. As pointed out by several people, including Moore himself, this Law holds because it is a form of a self-fulfilling prophecy and part of a strategic game. Since within the semi-conductor industry the mutual expectation exists that Moore's Law will continue to be realised, resources and efforts are allocated and directed in such a way that the individual firm at least can stay on this competititive line. Another example of agenda-related stability might be the development of off-shore wind technology. Although not many actors are yet involved in off-shore wind technology, and not many off-shore parks have yet been realised, everybody in the wind energy community seems to agree that off-shore wind technology is the logical 'next step', and therefore the expectation is justified that this step will be taken.

3.3.5 Indicators of stability

Based on the considerations above a list of indicators for stability can be established. The first indicator (related to the assessment of the system stability of a technology) is the robustness of a technology with regard to the overal societal agenda, of which an example has been given in the foregoing section (see Table 3.1 and Table 3.2). Indicators for convergent stability can be divided in 5 actor-related indicators, 2 artefact-related indicators and 3 agenda-related indicators.

Actor-related indicators
The first actor-related indicator is the *size of the specific technological community*. With many networks and actors in a technological community the chances are greater that fruitful relations will be established than in a community with only a few actors. If certain relations do not work out, other strategic partners might be found. In addition large communities are less vulnerable than small communities for micro-level contingencies. If for instance there are only a few actors in the community, the discontinuement of the activities of one of them can have a major impact on the fate and the orientation of the technology as a whole. In communities that consist of many members such an event will have less impact. Actors will come and actors will go, but the stable development of the technology is not dependent on the failure or succes of one of the actors in the community.

The chance that fruitful links among members of a technological community will be established depends also on the degree of *actor-interrelatedness* (second actor-related indicator) of such a community. In communities with a low degree of interrelatedness, not many contacts exist between the different networks that constitute the community. In communities with a high degree of interrelatedness many formal and informal contacts exist between the different networks. The formalized contacts take place at conferences, seminars, interinstitutional committees, journals etc. The higher the degree of interrelatedness, the higher the chance that fruitful relationships will develop, that common goals are formulated and that actors choose to concentrate on the tasks needed.

Geographical distribution is the third actor-relaed indicator. A distribution over many different countries enhances the stability of a technological development, for several reasons. In the first place many different local contexts are present in such a community which means that country-specific contingencies that influence the interest for a technology in that country, do have less effect on the development of the technology as a whole. In the second place the distribution over many different geographical locations enhances the number of potential sponsors that want to contribute financially to the development of the technology. For geographical distribution being an enhancing factor in technology development, it is essential that enough communication channels between the different locations exist and that the size of the community is larger than a critical threshold, because otherwise the activities become isolated and scattered instead of widespread and stimulating.

A fourth actor-related indicator is the *actor-heterogeneity.* Since each technology is a socio-technical configuration, many heterogeneous links have to be established to let such a configuration work. Processes of technological development involve the creation and establishment of these heterogeneous links. This means that all kind of actors are needed, ranging from university researchers to governmental sponsoring or regulatory agencies to (prospective) users. The presence of many different kind of actors in an actor-network is not a guarantee for success but gives an indication of the networks ability to cope with the heterogeneous work that has to be done. Heterogeneity of actors is not only important for individual networks, but also for a technological community that is formed by representants of the different networks. If specific relations between actors in a network do not work out, new links with other members or networks within the technological community might be established. Short networks that are complementary might find each other and establish strategic alliances.

Not all members of a community, nor the micro-level networks they constitute, are equal. The change of activities, including the decision to discontinue the activities, of a dominant or central actor has more impact than if this is done by a peripheral actor or a small micro-level network. Therefore it is important to analyse the equivalent of the market structure or industry structure of a technological community (call it a *'networks structure'*). Networks structures with high concentration ratios will include a few dominant actors and peripheral actors. In such a case the stability of each of the networks that are established around these dominant actors should be analysed to say something more about the stability of the technology's development. Networks structures with low concentration ratios can be analysed at the meso-level of the technological community alone. It is not evident whether a high or low concentration ratio contributes or not to a stable technological development. Change and new ideas often come from newcomers in the field and are more easily adopted by peripheral R&D networks (because their sunk investments in certain directions are lower). Change and new ideas on the one hand are needed to find solutions to continue a historical trend. On the other hand change and new ideas might easily alter the focus of a technological community and the direction of a technological development. In industrial economics the degree of innovation of an industry is related to its concentration degree by an inverted U-curve, meaning that the most innovative industries have an average concentration ratio.

Artefact-related indicators
A first artefact-oriented indicator is the *degree and kind of materialisation of a technology*. As been said before, the orientation of a technological development is not easy to change if the technology is in widespread use (such as automobiles) or if large and expensive installations have been built (e.g. large power plants, or the large nuclear fusion research installations). Therefore an assessment of the kind of materialisation (e.g. commercial products or demonstrations or both) and the degree of materialisation (production statistics, market penetration rates, size of laboratory constructions) is needed.

A high degree of *technological interrelatedness* enhances the probability of a new artefact to be taken up and be further developed. As technologies become more adopted, a number of other sub-technologies and products become part of its infrastructure (Arthur, 1988). A kind of mutual dependency between technologies emerges, which enhances the stability of the technological development in question. Also the degree to which new technologies 'match' with existing technologies and infrastructures is important. It is only after new technologies have been taken up and embedded in 'old' structures that they are able to change these structures eventually.

Agenda-related indicators
The first agenda-related stability indicator is the *dominant learning parameter*. Most of the time costs are important learning parameters, but sometimes other issues are more important, such as for instance safety for nuclear installations, noxious emission reduction for coal-fired powerplants, comfort and safey for cars.

A second agenda-related indicator for stability is the *prospective application* of a technology. Which applications are foreseen and what type of technology is seen as most fit for what type of application? Do the opinions on these technology-application combinations converge or not? Last but not least the existence in a community of a *prospective chronology* can tell something about what the community expects to happen in the future. Is there a dominant vision on 'the next step'? To what extent are these visions shared?

Table 3.3 *Stability indicators*

Actor-related indicators	Artefact-related indicators	Agenda-related indicators
The number of networks involved	degree and kind of materialisation	dominance of learning parameters
The interrelatedness within the technological community	degree of technological interrelatedness	the degree of consensus on future type-application combinations
The geographical extension of the technological community		the degree of consensus on prospective chronology
The heterogeneity of the actors		
The heterogeneity of actors		
The networks-structure of the technological community		

By systematically checking this list of indicators for different technologies and comparing the outcomes, the relative stability of one technology with regard to another can be assessed. Remaining issues in the design of a stability analysis tool are how to score the different indicators and how to weight the different answers with regard to each other. There are several ways to get the information needed to assess the value of each of the indicators, varying from expert input to text analysis of articles and scientometric techniques. Table 3.4 gives an overview per indicator.

Table 3.4 *Indicators, sources, methods and scoring*

Indicator	Sources	Methods, scoring
Number of networks	Databases, interviews, introductions and acknowledgments in papers	Number of authors or papers. Links between authors by text analysis
Heterogeneity	Actor-descriptions in titles and introduction papers.	Define different poles (e.g. Science, Technology, Users, Regulation, etc.) Count.
Actor interrelatedness	Interviews, references, dedicated databases	Number and frequency of seminars, journals, international committees (e.g. IEA-Annexes, etc.)
Geographical extension	Paper headings of papers in databases	Number of countries involved
Networks-structure	Databases	Number of papers per actor; Herfindahl-index
Degree and character materialisation	Interviews, review papers	Installed units, number and size of research structures
Technical interrelatedness	Interviews, (review) papers	Description of related existing technologies and sub-technologies needed
(Dominance) learning parameters	(Review) papers, comparing expert opinions by interviews	Description of parameter and its historical dev. trends + degree of consensus
(Dominance) prospective type-applications combinations	(Review) papers, comparing expert opinions by interviews	Description type-application combinations + degree of consensus
(Dominance) prospective chronology	(Review) papers, comparing expert opinions by interviews	Description labeling types in 'generation, + degree of consensus

3.4 Application of the approach to three energy technologies

A complete stability analysis for a technology is a rather laborious task. However, not in all cases it is needed to review every stability indicator in detail to know whether a technological development is stable or not. The list of stability indicators and the triple-A triangle (see Figure 3.2) should rather be seen as resources that provide conceptual and analytical tools to perform (partial) stability analyses in order to be able to say more about the basic questions listed in 3.3.1. In the following sub-sections the four questions (is there a historical trend, can it be expected that the development will continue at all, can it be expected that the development will not change its direction, can it be expected that the development will continue at the same speed (i.e. will it have the same progress ratio) as in recent history?) will be applied to four technologies: wind, PV, gas turbines and fuel cells (for the reasons for the choice of these technologies see Chapter 4).

3.4.1 Wind turbines

Is there a trend from which a historical progress ratio can be determined?
Since the early 1980's there has been a market for wind turbines created and sustained by subsidies and stimulation schemes in several countries. Over the period 1982-1995 Neij (1997) reports a progress ratio of investment costs of.96 and of kWh-costs of 0.91 percent. However, it is not clear from the article whether she has calculated this progress ratio in nominal or real terms. At ECN an analysis has been made by dividing the annual turnover of the Danish Wind Turbine Industry by its annual output in MW (these data are freely available at the Danish Wind Turbine Manufacturers Association Internet Site). This method yields a progress ratio of about 0.95 in nominal terms and of 0.87 (using the Danish consumer price indices) in real terms of the wind turbine investment costs. The value of 0.87 for investment costs alone means that an even lower progres ratio can be expected for kWh costs from wind. Sorensen (1997) reports about a value of this progress ratio of 0.80.

The value of 0.87 is as good as the statistics are. The industry turn-over method might not be completely reliable, since these statistics might also include the delivery of components, services and other things that are not directly related to the investment costs of wind turbines. Currently at ECN a database of market prices of wind turbines at the German market is under construction. The analyses carried out with these data will shed some more light on the value of the historical progress ratio. In order to avoid to be overoptimistic for the time being the progress ratio is estimated at 0.90

Is it plausible that the technology will continue to be developed at all?
The answer to this question can be a clear yes. The expected system stability will remain large since wind energy can contribute to one of the major issues on the international political agenda (climate change). Also in case the political agenda will leave the climate issue and retake the issue of finite resources, or other environmental emission problems, wind energy can continue to play a role and will continue to be stimulated. The convergent stability of the development of wind energy technology is ensured by the large number of actors (in many different countries) that are involved in its development, the large degree of materialisation in terms of growing number of wind turbines installed each year, the maturing structure of the wind turbine industry (with around ten large producers and many component suppliers) and because of the on-going geographical expansion of

markets for wind turbined (reducing the risk of contingencies with regard to wind turbine stimulation programs in specific countries).

Will the direction of the development remain the same or will its course be altered?
Investment costs, performance and noise reduction have been the major focusses of development. There is no reason to believe that this will change, at least not for on-shore wind turbines. For off-shore wind turbines the noise-issue is less relevant, which will allow a further increase in performance. On the other hand off-shore wind turbines might require some adaptation to new environments, requiring new learning experiences. The focus might shift to the development of turbines that require as little maintenance as possible.

Is it plausible that the progress ratio observed will stay the same, or will it decrease/ increase?
In periods of high R&D intensities (e.g. expressed in $ R&D/kW sold), the progress ratio in general is lower than in periods of lower R&D intensities (see e.g. Messner, 1997), given that the structure of the technological developments do not change. In the case of wind, however, one of the stability indicators, i.e. the actor-interrelatedness is about to change in a certain sense. As Jorgensen and Karnoe (1995) report, during the 1980's and the early 1990's the wind turbine community in Denmark has been split up in two. The first line of development was a top-down approach, a line of planned research and development programmes which were aiming at the design of the 'optimum' wind turbine of sufficient size directly. This approach has resulted in several large R&D wind turbines in the range of 1 MW to 3 MW. This strategy has not yielded cost-effective wind turbines. The other approach was a bottom-up approach, based on learning-by-doing/using etc. in which the small turbines were scaled-up step by step. Jorgensen and Karnoe report that between 1978 to 1989 the second approach was sustained by the government with 210 million Dkr of market support and 116 million Dkr of research support for innovation. All the other R&D expenditures have been in the realm of the top-down approach, and thus have not contributed to the costs decrease of wind turbine prizes. Also in other countries the two different approaches existed. Several large R&D wind turbines have been constructed e.g. in Germany, the United States and Sweden. In determining the R&D intensity of the wind turbine development these figures should not be taken into account.

What does this mean for the future R&D intensity and progress ratio of wind turbines? What can be observed is that the two lines currently come together. The bottom-up approach has led to wind turbines in the size of 1 MW to 2 MW, the same size as the top-down approach has been aiming at from the early 1980's on. This means that some knowledge needed for the optimisation of large wind turbines has already been generated in the past, that test facilities are already available and learning experiences with the operation of large wind turbines for longer period has already been gathered. This means that in the short term it can be expected that some of the gains of past top-down approach efforts will have a positive influence on the progress ratio of wind turbine development. This means that it can be expected that the progress ratio of wind turbines will at least remain the same in the future, and not become less favourable, as might be expected from the argument that wind turbines are still in an 'R&D phase' (Messner, 1997).

3.4.2 PV

Is there a historical trend from which a historical progress ratio can be determined?
As reported by Neij (1997) Williams and Terzin (1993) have determined the progress ratio for PV of 0.82 for the period 1976-1992. ECN-data on the period between 1980 and 1995 show a value of 0.81 (see Chapter 4). What is interesting is that Neij reports about another study (Cody and Tiedje, 1997) covering the period 1976-1988, that leads to a progress ratio of 0.78. This lower progress ratio probably is due to a higher R&D intensity in terms of R&D dollars per kW sold on the market in the period 1976-1988 than in the period 1976-1992 or 1980-1995.

Is it plausible that the technology will continue to be developed at all?
Again a clear yes, for the same reasons as mentioned for wind.

Will the direction of the development remain the same or will its course be altered?
There is no reason to believe that the focus on cost reduction and performance improvement will change in the development of photovoltaics.

Is it plausible that the progress ratio observed will stay the same, or will it decrease/ increase?
As the market is growing fast each year (a 40% increase between 1996 and 1997 (De Lange, 1998)) the R&D budgets should rise at a same pace to keep the progress ratio on track. There are signs that this is going to happen. The Netherlands budget for PV for instance has doubled recently (De Lange, 1998). But in the long term, as the market growth goes on, research funding might shift from public research to private research (with less open interaction between the different research activities) and the overall R&D intensity might decrease. This means that it cannot be expected that the progress ratio of PV will become much lower than 0.81.

3.4.3 Fuel Cells

Is there a historical trend from which a historical progress ratio can be determined?
The development of fuel cells until today has mainly been an R&D-oriented development. With the exception of applications in spacecraft there has been barely any market introduction efforts untill the early 1990's. Since a few years a few hundred 200 kW installations have been sold on the global market. What can be determined is a trend over time (see Figure 3.3, derived from Schaeffer, 1998). With the help of an internal crude estimation of the cumulative capacity of all kinds of demonstration fuel cells during the years (also based on Schaeffer, 1998), the progress ratio for the period 1962-1997 can be estimated to be 0.66. This low value reflects the high R&D intensity of the development of fuel cells. It also illustrates that a low progress ratio is not always favourable for the technology, because this progress ratio is achieved by producing very little capacity and allocating much R&D to the technology. In this way the time it takes to get to a commercial product might take many decades. The only commercial manufacturer of fuel cells claims to currently achieve a progress ratio in its manufacturing of fuel cells of 75% (Whitaker, 1998).

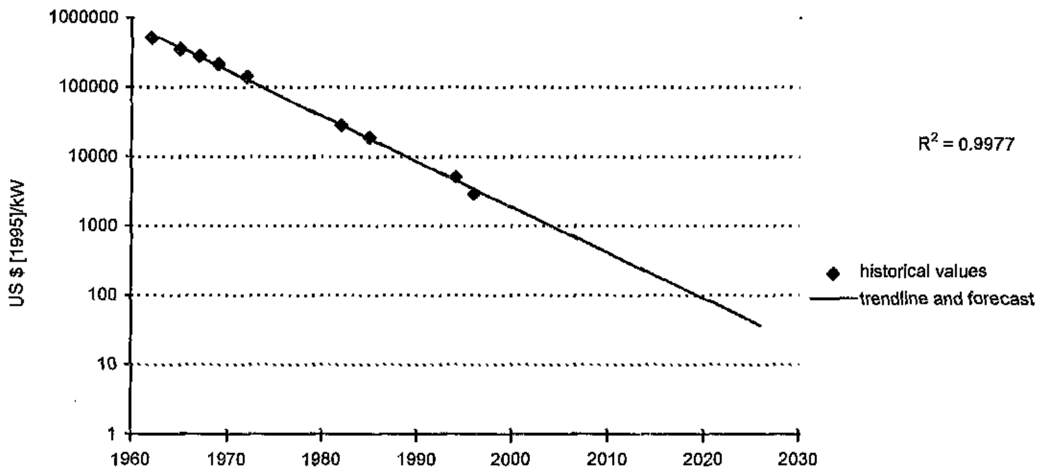


Figure 3.3 *Historical specific costs of fuel cells*

Is it plausible that the technology will continue to be developed at all?
There are many reasons why the answer to this questions can be confirmed. The fuel cell is currently getting much attention and is widely seen as one of the technologies that can significantly contribute to the resolution of the climate change issue. As has been explained in 3.3.2 fuel cells have achieved a large degree of stability by a complex kind of actor-dynamics. Most of the stability actor-related stability indicators point to a continuing number of activities in the fuel cell area. Recently the involvement of the automobile and oil industry and their commonly shared expectation that there will be fuel cell cars for sale in 2004 have introduced an important strategic game component into fuel cell development. Because of the mutual expectation among the automobile manufacturers that the competitors will strive for a commercial fuel cell car by 2004, large resources are directed to achieve this goal, in order not to miss the boat.

Will the direction of the development remain the same or will its course be altered?
Costs and performance (in terms of efficiency and power density) will remain the major issues in research.

Is it plausible that the progress ratio observed will stay the same, or will it decrease/ increase?
It is not very plausible that, as markets for fuel cells will be developed, the progress ratio will remain on the low historical values of 0.66 or 0.75. An estimation that is in line with this insight (Thomas, James and Lomax, 1998) gets to a progress ratio of 0.82 This result is based on an expert estimate of how much a fuel cell car will cost when produced in series of 300,000 cars, compared to an estimation of what the current production of one single car would cost. Out of these estimation a progress ratio can be calculated.

3.5 Summary and conclusions

In this chapter several generic issues that are encountered when implementing endogenous technological learning into energy models have been discussed. In the first place the need for endogenous alignment of technology characterisations has been discussed. In addition an approach to perform this alignment i.e. by defining key technologies has been proposed. In the third place the appropriate level of aggregation of technology descriptions in model databases has been discussed. Fourth, the importance for a balanced choice of learning technologies has been emphasised.

In addition to these generic issues a broad framework has been presented that can help in assessing whether observed historical trends can be expected to continue and can be used in energy modeling activities. The application to three energy technologies has illustrated that no extensive analysis is needed for each technology. A short analysis can be sufficient to decide wether historical or higher or lower values of progress ratios will be the best estimate for the future.

The conclusions with regard to the three technologies is as follows: the progres ratio of wind turbines will at least stay the same, and might decrease in the near future as the benefits of a separate top-down development line will become available to the prevailing bottom-up development line. The progress ratio of photovoltaics might increase a little as the technology is moving from a R&D-oriented period to a market-oriented period, but it might also stay the same (0.81) since the exponential market growth is accompanied by a growth in R&D expenditures as well. For fuel cells the estimation of the value of the progress ratio of 0.82 corresponds well to the observation on the one hand that hitherto the development of fuel cells has been largely R&D-oriented (implying that future progress ratios will be less favourable) and at the other hand the most recently observed value of the progress ratio is 0.75.

4. TECHNOLOGY LEARNING IN MARKAL-EUROPE

Testing the performance of a concept for endogenised technology learning for MARKAL modelling purposes sets specific requirements to the model database used. Several arguments favoured the selection of the recently developed MARKAL-EUROPE database, as already presented in Section 2.3.

Obviously, the incorporation of the concept of endogenised learning into the MARKAL database requires additional data on specific technology learning parameters. Furthermore, a selection is needed of technologies for which endogenisation of technology learning could be appropriate. This implies that a selection procedure has to be developed and applied, using criteria defining whether endogenisation of technology learning for a technology is appropriate or not.

In the first section some criteria are discussed which can be used to select technologies for which endogenisation of technology learning is appropriate. One of these criteria refers to technologies being a key technology within prospective energy systems. Therefore, the second section describes the selection of key technologies from the MARKAL-EUROPE database, refering to the methodology for technology characterization described in Chapter 3. In Section 4.3 key technologies are choosen which match the selection criteria for endogenisation of technology learning. For these technologies the learning parameters required for the learning version of MARKAL and other modifications of the MARKAL-EUROPE database are determined. The chapter is concluded with main findings in Section 4.5.

4.1 Criteria for endogenisation of technology learning

Learning of energy technologies refers to improvement of technology parameters, as for instance costs, performance and reliability, for every newly produced unit. Obviously, improvement of energy or environmental performance could require higher investment costs. Here, endogenisation of technology learning is limited to endogenisation of the relationship between investment cost reduction and the total amount of produced units (cumulative installed capacity).

Technologies which are currently in the end-phase of technology development, as for instance steam turbines, only show small reductions of investment costs for newly installed units. Applying endogenised learning for these technologies will not largely influence the MARKAL model outcomes, since improvement of investment costs can be assessed quite accurately and exogenously included in the model database. Therefore, some criteria have to be defined which can be used to select technologies for which endogenisation of technology learning could be beneficial for our modelling purposes.

It appears that endogenisation of technology learning is appropriate for technologies which match (one of) the following 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; key technologies are here defined as technologies which are clearly distinctive with respect to the applied energy conversion process (see also Sections 3.2.2 and 4.2),
- presence of a direct competing technology with endogenised learning.

Conceptual technology development characterization issues, as discussed in Chapter 3, help to analyse whether technologies match the above described criteria or not. For instance, it can be seen that solar cells could match with the selection criteria. Solar cells are in an early phase of technology development, whereas large potentials for investment costs reduction are anticipated. Furthermore, implementation of solar cells could induce large environmental benefits and can be seen as a key technology for small scale demand side applications, as well as for large scale power supply side options. Endogenisation of technology learning for solar cells necessitates also the incorporation of technology learning for wind power: technology learning of wind power could be closely linked to the market development of solar cells, since both technologies operate on the renewable electricity market.

It appears that all technologies which are currently included in the MARKAL-EUROPE database are based on specific applications and combinations of key technologies. This implies that technology development and, related, the market prospects of database technologies are extensively determined by key technologies incorporated in them. Therefore, Section 4.presents key technologies from the MARKAL-EUROPE database which are relevant with respect to technology development.

4.2 Selection of key technologies

The database MARKAL-EUROPE consists of more than 500 energy technologies, conscientiously selected to realize modelling objectives as the assessment of future prospects for energy technologies and energy policy instruments. Usually, for one specific technology a variety of potential markets or applications can be defined. For instance, in the MARKAL-EUROPE database three distinctive solar cells are specified, i.e. solar cells located in Middle Europe, solar cells located in Southern Europe and solar cells located in Southern Europe generating electricity for the rest of Europe. The distinction is based on the fact that the performance of solar cell systems strongly depends on the prevailing intensity and amount of sun hours. This implies that solar cells located in Southern Europe have considerably higher capacity load factors than solar cells located in the rest of Europe. Obviously, extra costs and losses arise if the electricity produced is transported over long distances. Consequently, electricity generation costs of solar cells can vary substantially over the European continent, which justifies the applied distinction into three categories.

The MARKAL-EUROPE database actually consists of a limited amount of so-called key technologies. Key technologies are here defined as technologies which are clearly distinctive with respect to the applied energy conversion process. E.g. the electric heat pump is considered to be a key technology for future energy systems: the database consists of about 20 distinctive electric heat pump applications, varying from applications for households (heating, washing/drying, combination with solar boiler), services (heating for small and large size buildings) and the industry (low temperature heat for small and large size applications). Other key technologies in the database are for instance gas turbines (peaking plants, CHP units, combined cycle units, integrated gasification units), industrial boilers, boilers for residential applications, steam turbines, gasification processes and burners.

All technologies which are currently included in the MARKAL-EUROPE database are based on specific applications and combinations of key technologies. This implies that technology development and, related, the market prospects of database technologies are strongly determined by key technologies. When technology learning is considered to depend on the market development of technologies (i.e. cumulative installed capacity), it should be realized that technology learning of a specific key technology is determined by the market development of all technologies in which that specific key technology is applied. Therefore, the incorporation of the concept of endogenised technology learning into a bottom-up model requires definition of key technologies. Moreover, endogenisation of learning of a specific key technology links learning of different technologies in which the key technology is applied. As an illustration, this facilitates the analysis of the role of niche-market development on technology development as a whole.

From the MARKAL-EUROPE database a set of key technologies can be derived, which are currently included in the defined database technologies and representative with respect to technology development. Table 4.1 provides an overview of selected key technologies.

The conceptual technology characterization issues as described in Chapter 3 helps to overlook small technology differences which do not substantially direct the development of technologies. A distinction between unit sizes (low and high capacity wind power), performances (new gas turbines, high efficient residential boilers) or materials applied (solid oxide fuel cell, molten carbonate fuel cell) should only be applied when they are considerably directing the technology development process. On the other hand, to facilitate incorporation of the concept of endogenised technology learning with an adequate defined database, the model user is enforced to analyse the technologies of the model database much more from a component point of view, since many key technologies are embodied in database technologies as their main components.

In the next section key technologies are chosen which match the selection criteria as discussed in section 4.1.

Table 4.1 Overview of key technologies MARKAL-EUROPE database (indicative)

Key technology	Supply technology/ Demand device
Nuclear reactor	supply
Gas turbine	supply
Hydro-turbine	supply
Steam turbine	supply
Wind turbine	supply
High capacity (power generation, industrial) boiler	supply
Gasifier	supply
Solar cell	supply
Fuel cell	supply/demand
Burner	supply/demand
End-of-pipe flue gas cleaning process	supply/demand
Electric heat pump	demand
Absorption heat pump	demand
Internal combustion engine	demand
Electric motor	demand
Battery	demand
Heat exchangers	demand
Low capacity (buildings, households) boiler	demand
Solar boiler	demand
Coated glass	demand
Insulation materials	demand

4.3 Selection of key technologies with endogenised learning

Some of the selected key technologies as listed in Table 4.1 are already in the end-phase of technology development (reduction of investment costs), as for instance steam turbines and industrial boilers. Others are currently mainly learning on performance parameters (burners, gas turbines) or still R&D driven with respect to technology development (solar cells, fuel cells). The criteria for endogenisation of technology learning discussed in Section 4.1 can be used to select key technologies for which endogenisation of technology learning could be appropriate. The impact of endogenised technology learning on the computational performance of the MARKAL model obliges us to limit the amount of technologies for which endogenisation of technology learning can be applied. Table 4.2 gives an overview of selected technologies for which endogenisation of technology learning will be applied in the experiments reported here.

Table 4.2 *Overview of selected key technologies with endogenised learning*

Key technology	Comments
Wind power	Omit old/new distinction, only on-shore
Fuel cell	Omit fuel cell type, only transportation
Solar cell	Omit different applications EU-region

The selection is based on several arguments: for wind power, fuel cells and solar cells a large potential of technology learning (reduction of investment costs) is expected. Furthermore, they are key technologies in many defined database technologies. Wind power and solar cells are direct competitors on the renewable electricity market. Fuel cells can be applied for supply side options as well as for demand side applications. Gasturbines also match the criteria. Gas turbines currently mainly learn on performance parameters (efficiency), but are a key technology in many defined database technologies and therefore relevant for analysis of the impact of niche-market development on technology development as a whole. Gas turbines are not yet defined as key technologies in the MARKAL-EUROPE database, but modelled as components within energy technologies. Therefore, gasturbines are in this stage of the learning experiments not yet taken into account. Also wind power, fuel cells and solar cells are not yet defined as key technologies, but modelled as single technologies representing the similar options for these technologies in the MARKAL-EUROPE database.

4.4 Determination of learning parameters

Incorporation of the relation between investment costs and the total amount of produced units (cumulative installed capacity) in the MARKAL model requires definition of additional equations and additional data on specific technology learning parameters (see section 2.2.3). Actually, the learning curve as implemented in MARKAL requires 4 parameters related to technology learning:

1. technology progress ratio,
2. initial investment costs of the technology in start year,
3. initial cumulative installed capacity of the technology in start year,
4. maximum cumulative installed capacity of the technology over entire time horizon.

For technologies which are already operational, historical data on the development of investment costs and installed capacity can be collected and analysed. ECN developed a accounting framework to determine learning parameters from historical data. Analysis of data on the historical development of investment costs of technologies, such as wind power and solar cells, indicated that the determination of learning parameters based on historical data should be carried out carefully. 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 through market penetration. Extrapolation of R&D oriented phase data (of for instance solar cells) could lead to an overestimation of technology learning.

Characterization of technology development, as described in Chapter 3, supports adequate analysis of historical data. Moreover, it allocates the main factors influencing technology learning, which helps to estimate learning parameters for technologies for which historical data are inaccurate or lacking, since not yet available on the market. Another basis for estimation of learning parameters can be found in the development of investment costs of technologies included in bottom-up models as for instance NEMS (EIA, 1998), GENIE (Mattson, 1998), MESSAGE (Messner, 1997) and POLES (Criqui, 1998).

The historical world-wide development of investment costs of wind power, gas turbines and solar cells follows a learning trend (see Figure 4.1-4.3), showing that at every doubling of cumulative installed capacity of these technologies the investment costs declined more or less at a constant rate. The progress ratio can easily be assessed from trend line approximation of the historical data. The historical data of the gas turbine show two phases, which are different with respect to the progress ratio. The progress ratio of the second phase (0.9), which is often considered to be the phase directed by market development, is larger than the overall progress ratio (0.88). Figure 4.4 shows the large impact of the progress ratio on the development of the investment costs. The progress ratio of wind power (0.9) is quite large compared to the progres ratio of gas turbines (0.88) and solar cells (0.81).

The initial investment costs can be taken from time serie analysis of the cumulative installed capacity of the technology, using the trend line approximation, while for the initial cumulative installed capacity of existing technologies EU statistics could be used. For candidate technologies which are not yet available on the market, a suitable start value for the initial cumulative installed capacity has to be chosen. The value of the maximum cumulative installed capacity over the entire time horizon could be derived from physical bounds on the installed capacity or a maximum market share in the end year.

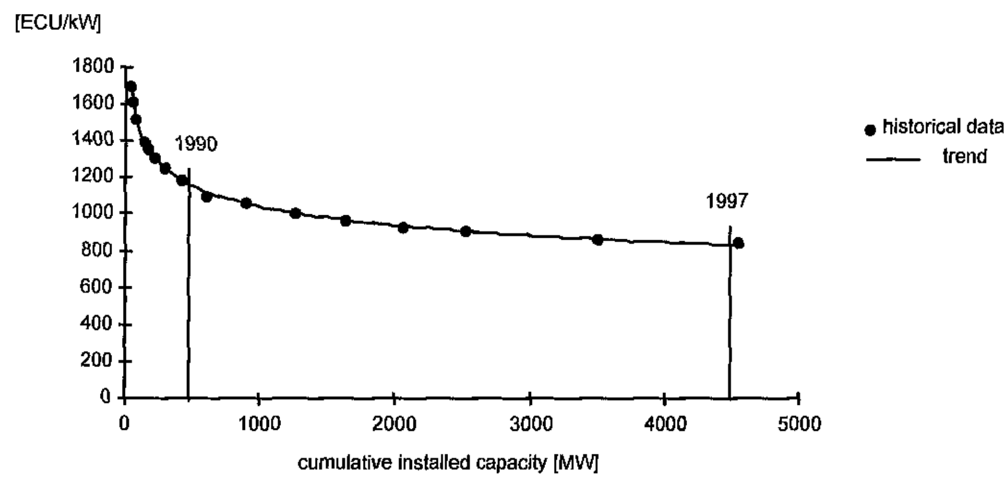


Figure 4.1 *Development of investment costs wind power world wide (De Lange et al., 1999)*

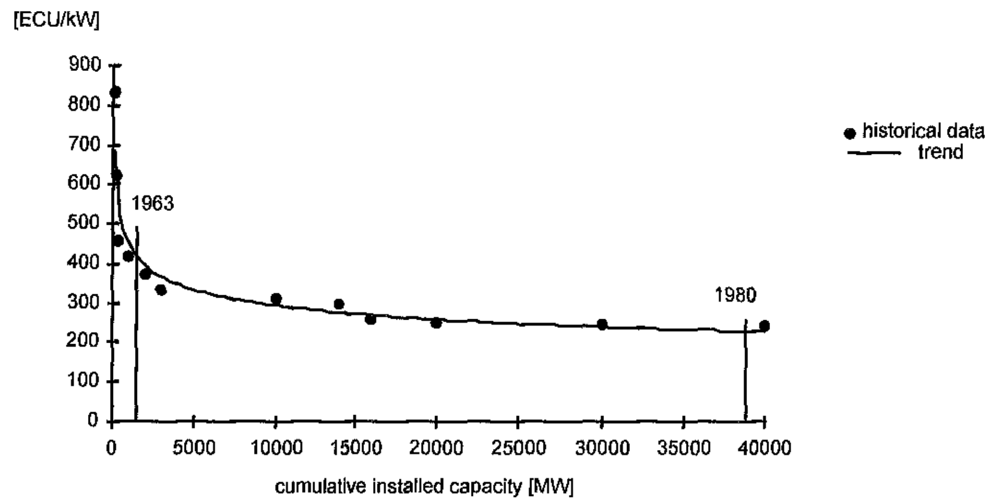


Figure 4.2 *Development of investment costs gas turbine world-wide (Messner, 1997)*

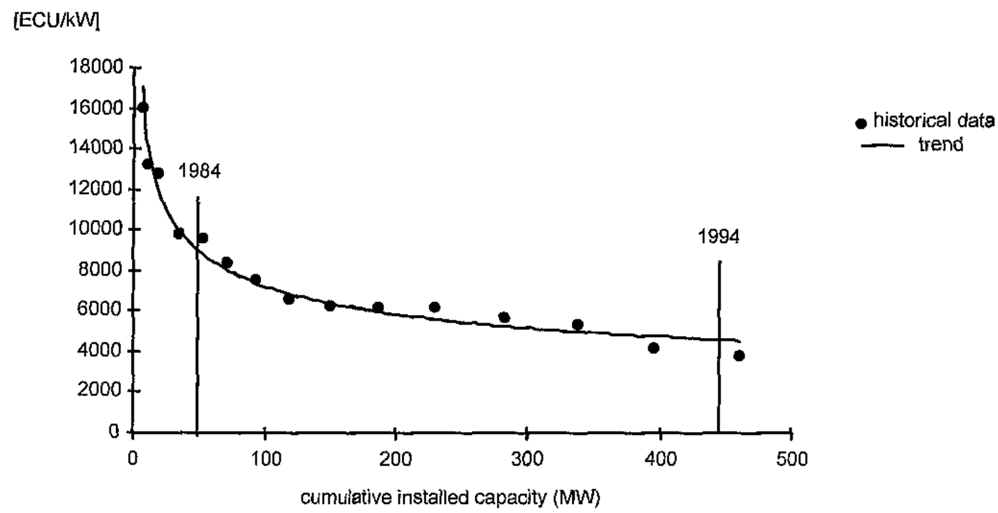


Figure 4.3 *Development of investment costs photovoltaic cells world wide (Bos et al., 1999)*

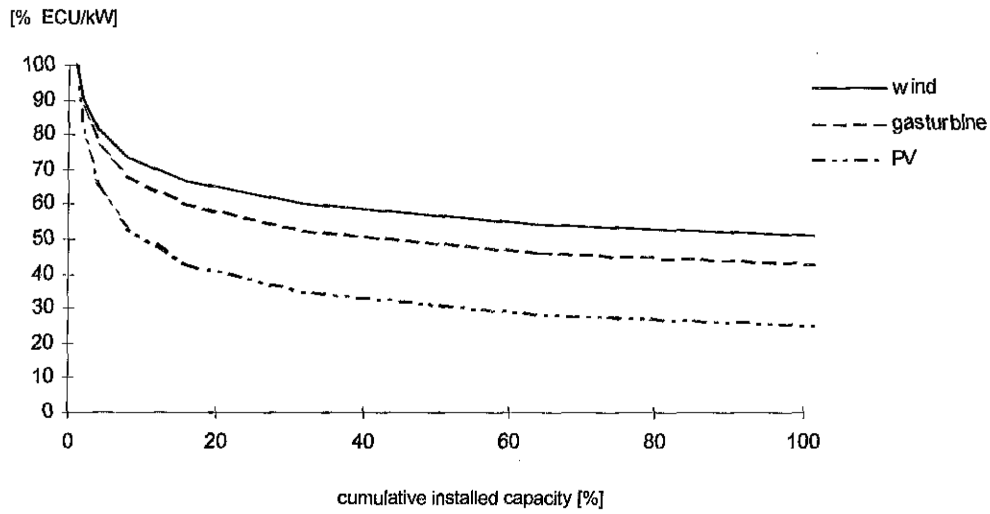


Figure 4.4 *Comparison of technology learning on investment costs of wind power, gas turbine and photovoltaic cells*

In Table 4.3 the values of the technology learning parameters as chosen for the base case model runs are given. The progress ratios and initial investment costs of wind power and solar cells are based on the above presented trend lines. The initial values for the investment costs and the cumulative installed capacity of fuel cell cars are not well known. Therefore, the learning parameters of the fuel cell car, as given in the Table 4.3, are also based on expert ideas about end-values of the investment costs and cumulative installed capacity. Actually, the minimum achievable end-value of the investment costs, coming to about 8840 ECU/veh, is lower than the current average investment costs level of gasoline cars (11000 ECU/veh), whereas the end-value of the cumulative installed capacity (1030 PJ/yr) is in line with the current demand for gasoline cars in the EU.

Incorporating endogenised technology learning for gas turbines first requires definition of the gas turbine as a separate key technology in the model database. Therefore, at this stage of the project endogenised technology learning is not yet applied to the gas turbine.

The amount of possible doublings (n) of the cumulative installed capacity, as indirectly set by the initial value and end-value of the cumulative installed capacity, is illustrative for the maximum potential of technology learning as given to a technology. Obviously, the factor n depends from the region modelled. For instance, gas turbines have, as part of many installed combined heat and power technology, already taken a large share of their potential market in the Netherlands. Therefore, the factor n for gas turbines is substantially smaller for an energy system model of the Netherlands than for a world model. This could lead to inconsistent assumptions on technology learning parameters for the Netherlands, since technology learning of gas turbines is directed by global market development. The modeler should be aware of the impact of such inconsistencies, induced by regional differences, on the model results.

Table 4.3 *Values of technology learning parameters for wind power, solar cells and fuel cell car, as used for the Base case*

Technology	Wind (on-shore)	Solar PV	Fuel cell car
Progress ratio	0.90	0.81	0.82
Initial values			
Investment costs	950 ECU/kW	5000 ECU/kW	10745 ECU/GJyr (eq. to 78550 ECU/veh)
Cumulative installed capacity	5500 MW	100 MW	0.5 PJ/yr
Year	2000	2000	2000
End values			
Cumulative installed capacity	320000 MW	160000 MW	1030 PJ/yr
Maximum doublings n	5.9	10.6	11.0
Investment costs	522 ECU/kW	531 ECU/kW	1209 ECU/GJyr (eq. to 8840 ECU/veh)
Year	2050	2050	2050

4.5 Summary and conclusions

All technologies which are currently included in the MARKAL-EUROPE database (about 500) are based on specific applications and combinations of key technologies (about 20), i.e. technologies which are clearly distinctive with respect to the applied energy conversion process. This implies that technology development and, related, the market prospects of database technologies are extensively determined by key technologies. Therefore, incorporating the concept of endogenised technology learning into a bottom-up model requires definition of key technologies and thus a re-evaluation of the reference energy system.

Criteria to select technologies for which endogenisation of technology learning could be appropriate are the expected potential of technology learning of the technology, the expected impact of technology learning on modelling outcomes, the role of the technology as a key technology within prospective energy systems, and relevance of competition with other technologies for which endogenised technology learning is incorporated in the model.

Selected technologies matching the criteria for endogenisation of technology learning are the key technologies wind power, solar cells and fuel cell cars. For these technologies values of technology learning parameters, to be used for Base cases, have been assessed.

5. DEFINITION OF BASE CASE AND VARIANTS

This chapter presents an outline of the base cases and variants with which the MARKAL model with endogenous technological change has been tested on the MARKAL-EUROPE database. It should be noted that the underlying scenario and model results of these cases are not meant to derive policy recommendations on specific technologies or on any other aspects. The results (reported in Chapter 6) are solely meant to evaluate whether the concept of endogenous technological change is feasible for the MARKAL model, notably for relatively large and complex MARKAL databases.

5.1 Base case

The base case selected corresponds to the base case of the Rational Perspective (RP) scenario as outlined in (Ybema et al., 1997). For completeness, the next paragraph presents a brief description of this RP scenario. More details can be found in (Ybema et al., 1997).

Rational Perspective can be characterised as an ecologically driven scenario. The process of global economic integration will lead to more collective public action in this scenario. The cooperation between countries will be more efficient in order to deal with complex common problems. Heavy polluters and energy intensive industries will lose ground to more environmentally benign sectors like services. Widespread penetration of new, more efficient demand and supply technologies is facilitated. This strong penetration will be reached by setting efficiency standards, removing existing barriers for the introduction of efficient technologies and by active energy service companies which carry out cost-effective efficiency improvements for end-users, etc. The above mentioned policy shifts are driven by environmental concerns and concerns about efficiency throughout society. It is noted that the Rational Perspective base case does not assume specific policy to reduce CO_2 emissions.

The base case defined to evaluate the MARKAL model with endogenous learning incorporates some changes compared to the original RP base case; see Table 5.1. These changes have been implemented to obtain a case that is very well suited for comparison of various model formulations (e.g., models with and without endogenous learning) and for comparison of various input parameter values. Important changes are the aggregation of the solar PV technologies and large wind turbine technologies into one for each type. This as an approximation of the key technology concept that is not yet implemented in the model code; see section 4.2. As an alternative to using upper investment or capacity bounds in the model, maximum growth factors have been introduced in the model for all technologies with learning. A maximum annual growth rate of 20% was set for the installed capacity; see also Appendix A. These growth factors give the model flexibility to chose a capacity expansion trajectory and at the same time puts a cap on inter-period increases in capacity.

Table 5.1 *Changes compared to original base case Rational Perspective (MARKAL-EUROPE 1.0, Lako & Ybema, 1997)*

Technology or parameter	Change
Solar PV	One solar PV technology instead of the three solar PV technologies (for three different geographical regions of Western Europe)
Wind turbine	One wind turbine technology instead of the three original wind turbine technologies
Investment and capacity bounds	Removal of all investment and capacity lower and upper bounds on solar PV, fuel cell car, and large wind turbine technologies, except for: - the wind turbine lower capacity bound in 2000 (5.5 GW) and - the maximum investment bound on onshore wind turbines (reflecting a public planning constraint, assumed to amount to about 320 GW for the period 2000-2050)
Growth rate	Maximum annual growth rate of 20% for solar PV, fuel cell car, and large wind turbine technologies
Time horizon	Restriction to the first seven time periods 1990-2050, each period denoted by its midyear, e.g. 2000 stands for the years 1995-2005

It should be noted that market deployment controlling parameters like capacity and investment bounds and growth limits should be used carefully in conjunction with endogenous learning. For a more detailed discussion on this issue see Appendix A.

5.2 CO_2 policy variants

Policies to reduce future emissions of carbon dioxide (CO_2) can have a very large impact on the development of the future energy system (e.g., see (Ybema et al., 1997; IEA-ETSAP, 1997)). Since both the long term global targets for CO_2 emissions and the distribution of emission permits across the globe are uncertain, it is uncertain how much CO_2 is allowed to be emitted from Western Europe.

Two kinds of CO_2 policy variants have been defined, which merely serve to show their impact on the development of the future energy system:

1. The first CO_2 policy variant consists of posing a limit to the annual CO_2 emission from the year 2010 on. The limit used is taken as 8% below the 1990 level of emission (3224 Mt CO_2/year), and hence ends up at 2967 Mt CO_2/year. This limit should be regarded as illustration and not as an implementation of what the EU will do as follow-up to the Kyoto agreement. An alternative and perhaps more appropriate emission constraint would be cumulative limit (e.g. see discussion in Section 2.2 of (Lako et al., 1998a)). The purpose of these variants is to show the implications for the levels of investments in the technologies with endogenous learning, in particular for technologies that do not emit CO_2 (like solar PV and wind turbines).
2. A second variant assumes a CO_2 tax policy of 25 ECU/t CO_2 in 2010 and 50 ECU/t CO_2 in the periods 2020-2050. This variant leads to a lower emission path than with the 8% reduction variant, see Figure 5.1.

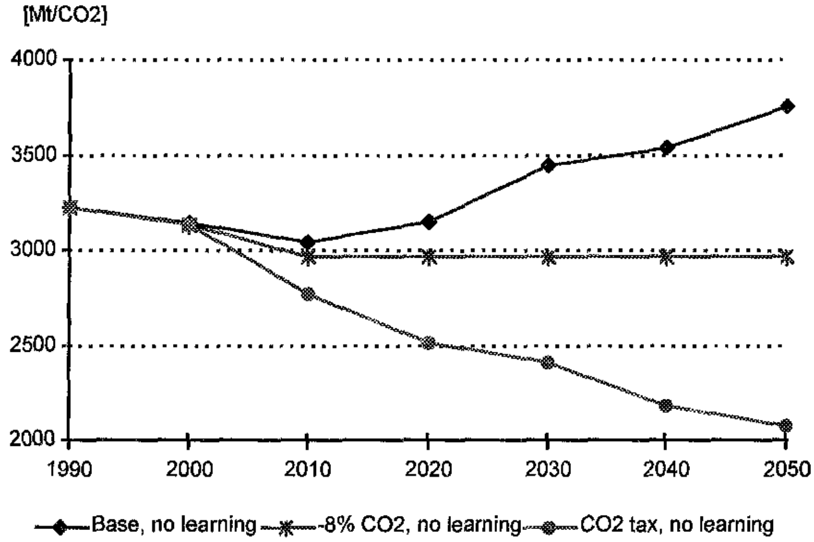


Figure 5.1 *CO_2 emissions in base case, CO_2 -8% case, and CO_2 tax case, conventional LP model without endogenous learning*

5.3 R, D&D variants

Adopting the concept of endogenous learning, several R,D&D linterventions can be considered that aim to speed up the market penetration of new technologies. Three types of R,D&D variants have been defined, each with the potential to lower the technology investment cost, such that the technology can become cost-effective within the time horizon of the model. For the sake of the assessment it is assumed the R,D&D activities will return the anticipated results.

1. *R&D leading to lower initial cost*
   Dedicated R&D efforts aimed at lowering the (initial) cost of a technology can speed up the pace with which it becomes competitive. For example, a technical breakthrough can imply a break in the cost trend. By comparing results in terms of overall system cost with and without the assumed R&D activity, its potential benefits can be assessed and compared against the R&D expenditures. To illustrate this option, the initial investment cost of the fuel cell car was lowered from 78500 ECU/veh to 58500 ECU/veh (about 25% reduction). Note that with the progress ratio assumed this cost reduction is the equivalent of a deployment impulse of about 3 times the initial cumulative capacity.
2. *Demonstration projects/Market stimulation*
   Demonstration projects could be a means to increase the experience with a technology and hence to reduce investment cost. Such experience can be factored into the model by adding a lower bound on the investment in new capacity in the first period(s), thereby forcing an accelarated learning trajectory. As an illustration, lower bounds on the capacity of solar PV has been set in the early periods (2000-2020) in an attempt to make it more cost-effective thereafter.

3. *R&D leading to better progress ratio*
   The progress ratio is the parameter indicating the investment cost reduction with each doubling of the cumulative installed capacity (sales) of the technology. Although the relationship of R&D and the progress ratio is unclear (in fact: the progress ratio and the experience curve concept are a representation of an aggregate of factors influencing the technology investment cost reduction), one could imagine a better (i.e. lower) progress ratio as a result of dedicated R&D efforts. It must be assumed that continued R&D supports are needed to bring about such a lasting improvement. As an illustration, the progress ratio of the solar PV has been reduced from 0.81 to 0.78, 0.75, and 0.72. Note that recently reported experiments with the GENIE model includes stochastic learning with respect to the progress ratio (Mattsson, 1998). Also, PSI has implemented a similar two-stage stochastic programming approach in the ERIS prototype (Kypreos & Barreto, 1998b).

The three R,D&D variants consider the possible impacts on technology learning; see figure 5.2 for an overview of their potential impact on future investment cost.

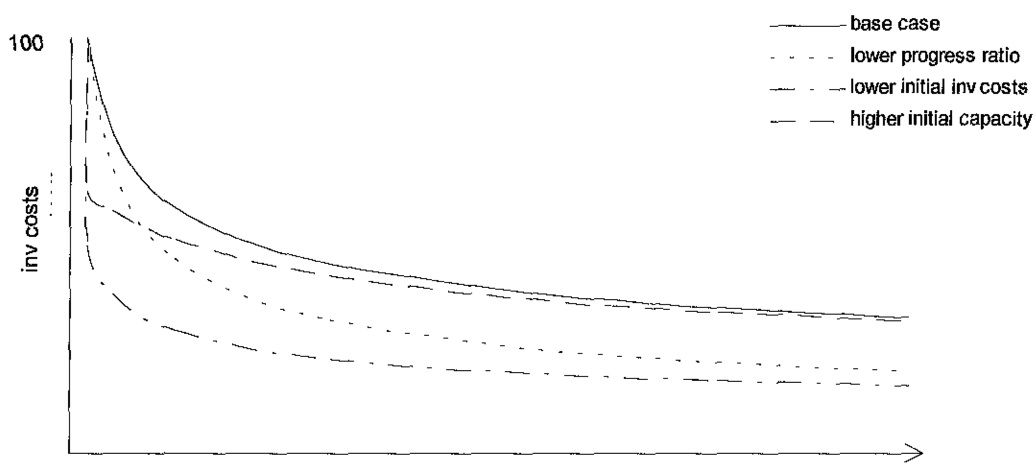


Figure 5.2 *Overview of the three types of R,D&D variants (indicative): lower initial investment costs (variant 1); higher initial cumulative capacity (variant 2); and lower progress ratio (variant 3)*

It should be noted that in all three cases above, the costs of additional R,D&D programmes can be compared with the benefits it could have on the energy system cost, thus enabling a cost-benefit analysis of such policy interventions.

5.4 Other sensitivity variants

Robustness of model results with respect to input data for key learning parameters is very important. In particular, small changes in parameter settings that generate solutions that are entirely different in the cost-effective technologies are not desirable. Therefore, a variety of experiments have been carried with the MARKAL-EUROPE MIP model to test the robustness with respect to the items outlined below.

Learning parameters
Each technology k with endogenous learning is characterized by four specific input parameters determining the investment cost development:
1. initial specific investment cost (SC_0),
2. initial cumulative capacity ($C_{k,0}$),
3. progress ratio (*pr*), and
4. maximum cumulative capacity ($C_{k,max}$).

The combination of these parameters determines the 'learning potential' of the technology. E.g. the ratio of maximum and initial cumulative capacity determines the number of doublings n, and hence the amount of possible cost reduction (pr^n). So, the minimum specific cost that can be achieved is:

$$SC_0 \times pr^n$$

Table 5.1 presents the maximum cost reductions for the base case; for more details see also Section 4.4.

Table 5.1 *Maximum cost reduction for wind power, solar cells and fuel cell car, as used for the Base case*

Technology	Wind (on-shore)	Solar PV	Fuel cell car
Initial values (2000)	950 ECU/kW	5000 ECU/kW	10745 ECU/GJyr (equivalent to 78550 ECU/veh)
End values (2050)	522 ECU/kW	531 ECU/kW	1209 ECU/GJyr (equivalent to 8840 ECU/veh)

Model formulations and accuracy of segmentation
In the course of this study, several alternatives of the MIP learning curve formulation have been tested. The results reported in the next chapter are based on the MIP formulation as added to the ERIS prototype by PSI (e.g. Kypreos & Barreto, 1998b, c, d). The main difference in the formulation ECN used is the alternative segmentation scheme (see also Section 2.3) to improve the behaviour of technologies at the very beginning of their learning curve. The number of segments and the segmentation scheme (location of kink-points) determine, together with the maximum cumulative capacity, the accuracy with which the MIP problem approximates the non-linear cumulative cost curve. A drawback of too many segments is the increase in the computational complexity as the number of integer variables increase with the number of segments.

Number of technologies
The MARKAL-EUROPE database has over 500 different technologies (about 40 supply-side conversion, 140 process, and 330 end-use technologies). It is not necessary to model all of these technologies with endogenous learning (if it would be feasible, given the amount of additional data needed, and it would require a total re-evaluation of the model to take into account the learning dependencies). However, the number of key technologies (about 20, as identified in Chapter 4) should, in principle, be modelled with endogenous learning. Two variants have been defined (with 5 and 10 technologies with endoge-

nous learning, respectively) to get an indication of the computational burdens associated with running a more complex MARKAL-EUROPE MIP model.

Discount rate
The discount rate used in bottom-up optimisation models like MARKAL is an important parameter that determines whether a technology becomes cost-effective or not. First, technologies with relatively high capital costs will less easily become cost-effective if a high discount rate is used. Moreover, the discount rate influences the balance between short term expenditures and long term benefits arising for example from learning In the base a discount rate of 5% is used. The use of a higher value would make a learning technology less attractive, and might even lead to a 'lock-out' as the future benefits are valued less than with a lower discount rate.

Solver options
The solution found can depend on the settings of the solver used for the MIP problem. For example, the Branch & Bound (B&B) algorithm of the MIP solver OSL requires a relative optimality criterion (OPTCR). If this criterion is (close to) zero the solution generated will be optimal. However, this may require an excessive number of nodes (branches) in the B&B algorithm, resulting in very large solution calculation times (CPUs) or very high memory requirements (RAM). If the number of discrete variables becomes too large (e.g. with many technologies with endogenous learning or with a very detailed segmentation scheme), solution times may be too large or the available memory may pose a limit. Generally, MIP problems are computationally far more complex than corresponding, similarly sized LP problems. The use of a less stringent optimality criterion may on the one hand lead to acceptable CPUs and RAM needed but on the other hand to non-optimal solutions. The use of an appropriate set of solver parameters can aid in generating optimal solutions within acceptable solution time and memory requirements. In particular, the solver parameter defining the strategy for deciding on branching in the B&B algorithm (STRATEGY) is important.

5.5 Summary of cases and variants

The next table summarizes the various cases and variants for the model runs reported and discussed in Chapter 6.

Table 5.2 *Overview of cases and variants*

Cases and variants	Section in Ch. 6	Description	Data changed compared to Base case
Base cases	*6.1*		
Base			
no learning		Base case without and	
learning		with endogenous learning	Learning data for 3 technologies
CO_2 policy cases	6.2		
-8 % CO_2		Annual CO_2 limit from 2010 on	Limit equals 92 % of 1990 level
CO_2 tax		Tax on CO_2 from 2010 on	Tax equals 25 ECU/tCO_2 in 2010 and 50 ECU/tCO_2 in 2020-2050
R,D&D cases	6.3		
SC_0 FCC -25%	6.3.1	Initial specific investment cost Fuel Cell Car down by 25%	SC_0 from 78500 to 58500 ECU/veh
SC_0 PV -40%	6.3.1	Initial specific investment cost solar PV down by 40%	SC_0 from 5000 to 3000 ECU/kW
CAP_{lo} PV	6.3.2	Lower capacity bound set on solar PV	
1-4			1 GW in 2000; 4 in 2010
1-5-10			1 GW in 2000; 5 in 2010; 10 in 2020
1-5-20			1 GW in 2000; 5 in 2010; 20 in 2020
pr PV 0.78, 0.75, 0.72	6.3.3	Progress ratio solar PV	from 0.81 to 0.78, 0.75, 0.72
Sensitivity cases	*6.4*		
$C_{k,0}$ FCC	6.4.1	Initial cumulative capacity Fuel Cell Car down by factor 1	from 0.5 to 0.1 PJ/yr
$C_{k,max}$ FCC	6.4.1	Maximum cumulative capacity Fuel Cell Car increased threefold	from 1030 to 3000 PJ/yr
06_lin, 06_log	6.4.2	Segmentation: Number and location of breakpoints:	all sensitivity cases are based
10_lin, 10_log		nn_loc, with nn=number and loc=lin (linear, equal distance) or loc=log (logarithmic)	on the CO_2 tax case
20_lin, 20_log			
0, 5, 10	6.4.3	Number of learning technologies	0, 5 and 10 instead of 3 learning technologies, all based on CO_2 tax case
Discount rate	6.4.4		from 5% to 2%
STRATEGY	6.4.5	OSL solver options for MIP: branching	from 48 to 1 (=OSL default)
OPTCR		strategy and optimality criterion	from 10^{-9} to 10^{-3}

6. NUMERICAL RESULTS

This chapter presents the results of the various cases and variants defined in the Chapter 5. Section 6.1 shows the results of the two base cases: one generated with the conventional LP model (without endogenous learning), and one base case employing the MIP model with endogenous learning. Section 6.2 presents the corresponding CO_2 policy variants, and compares the results with the base cases. Section 6.3 shows the results of the impact that R,D&D policies could have on the investment cost development of technologies with endogenous learning, and hence on their cost-effectiveness. Finally, Section 6.4 contains the results of the sensitivity analyses.

The indicators for comparing all of these cases and variants are:
- development of installed cumulative capacity (hence: of investment) of technologies with endogenous learning,
- cost development of these technologies,
- primary energy mix,
- electricity production sector, in particular the role of renewables (since two of the three selected technologies are renewable),
- CO_2 emissions,
- cost-benefit analysis of policy instruments like a CO_2 emission limit, CO_2 tax, and research, development, and demonstration (R,D&D).

6.1 Base cases

The base case of the LP model (without endogenous learning) is denoted by 'Base, no learning'. 'Base, learning' denotes the MIP model with endogenous learning.

Comparison LP model without learning versus MIP model with learning

All three selected technologies enter the solution for the 'Base, no learning' case, although for the fuel cell car and solar PV at negligible levels. These negligible levels are equal to the lower bounds set on the capacity. For the 'Base, learning' case, only the wind turbine enters the solution, with a stronger penetration than in the 'Base, no learning' case, see Figure 6.1. This is because with endogenous learning the investment cost can get much lower than was assumed in the 'Base, no learning' (LP, about 550 ECU/kW vs. 810 ECU/kW), see Figure 6.2. The investment level reaches its maximum according to the maximum investment bound on onshore wind turbines in the last five time periods 2010-2050. Over the entire time horizon the MIP model invests almost twice as much in wind energy than the LP model.

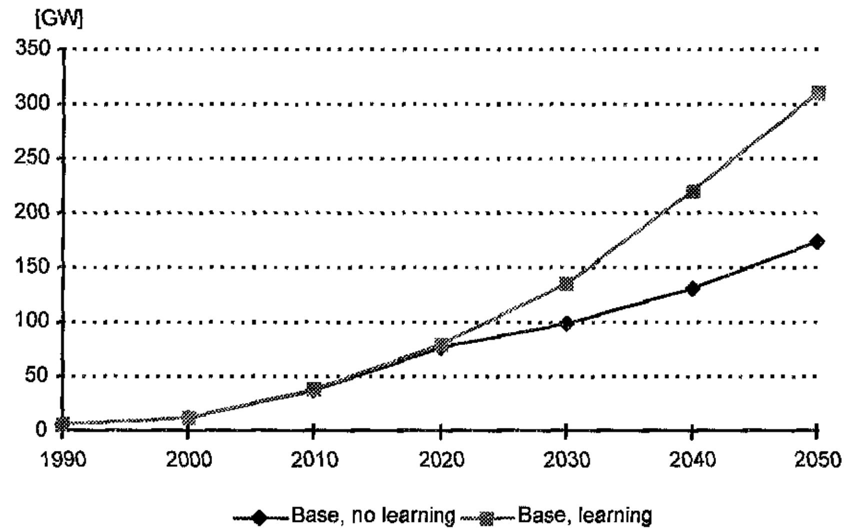


Figure 6.1 *Cumulative capacity wind in base case without (LP) and with (MIP) endogenous learning*

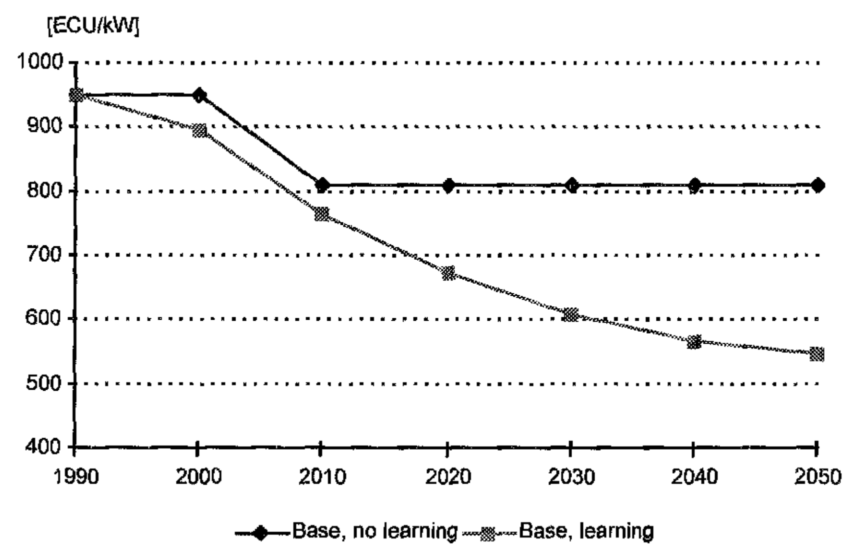


Figure 6.2 *Specific investment cost wind in base case without (LP) and with (MIP) endogenous learning*

6.2 CO_2 policy variants

The two CO_2 policy variants are labeled as follows: '-8% CO2, no learning' and '-8% CO2, learning' denote the variants in which the annual CO_2 emissions from 2010 and thereafter are 8% lower than the 1990 annual emission level. 'CO_2 tax, no learning' and 'CO_2 tax, learning' denote the variants in which a CO_2 tax is imposed starting from 25 ECU/tCO_2 in the period 2010 and 50 ECU/tCO_2 in the periods thereafter. The expectation is that a.o. renewable technologies will grow faster in the CO_2 policy variants. Other technologies expected to grow are natural gas based, energy saving, and more efficient technologies.

Comparison of base case versus CO_2 policy variants
The solutions with respect to wind energy are almost identical in all CO_2 policy variants, because wind energy is already at its maximum in the 'Base, learning' case during 2010-2050. The only difference is an increased investment in 2000, up to its maximum in the 'CO_2 tax, learning' case. As a result of the use of more wind energy (see Figure 6.1 in the previous section), the 'Base, learning' CO_2 emission level falls below the 'Base, no learning' case, see Figure 6.7.

Even with CO_2 emission limits or taxes on the model, the fuel cell car is still not cost-effective in both CO_2 policy variants, for both cases with and without endogenous learning. Possible reasons are: the initial costs are still too high, or the progress ratio (*pr*) is not small enough, or the cost reduction potential (see also Section 5.4, with prime indicator pr^n, n the number of doublings in cumulative capacity) is too low to arrive at competitive levels.

In the '-8 % CO_2' reduction variants, solar PV becomes barely cost-effective in the case with no endogenous learning. With a CO_2 tax imposed (the tax is much larger than the marginal reduction cost of CO_2 in the '-8% CO_2' case), solar PV becomes cost-effective, see Figure 6.3. In the case with learning,'CO_2 tax, learning', the maximum cumulative capacity (set to 160 GW) has already been reached in 2030. The model has no possibility to invest in the two periods thereafter (2040-2050), although it would be very cheap and cost-effective to do so. Such a solution is not considered realistic, as it depends entirely on the choice of parameters in the model. E.g. the maximum cumulative capacity could be set higher enabling a further expansion after 2030, or an investment upper bound per period could be used such that investments will be slowed down from 2020 to 2030 and postponed until later time periods. E.g. the ixpansion from 2030 to 2040 is now more than 100 GW; an investment bound of 40 or 50 GW per period could be set to smoothen the expansion.

The 'CO_2 tax, no learning' variant employs even more solar PV, see also Figure 6.3 and Figure 6.4 (c). This is because this case is not bounded by the maximum cumulative capacity, indicating the altready mentioned importance of bounds in the learning case above. In fact, the two cases cannot be compared, since the 'CO_2 tax, no learning' case has more potential for solar PV than the 'CO_2 tax, no learning' case. As a result, the total share of renewables in the electricity production becomes larger in the 'CO_2 tax, no learning' case, see Figure 6.4 and Figure 6.5. Consequently, the CO_2 emissions are less in the 'CO_2 tax, no learning' case than in the 'CO_2 tax, learning' case, see Figure 6.7. To compensate partly for the upper bound on solar PV, the 'CO_2 tax, learning' variant chooses gas based technology to reduce CO_2 emissions, see Figure 6.6.

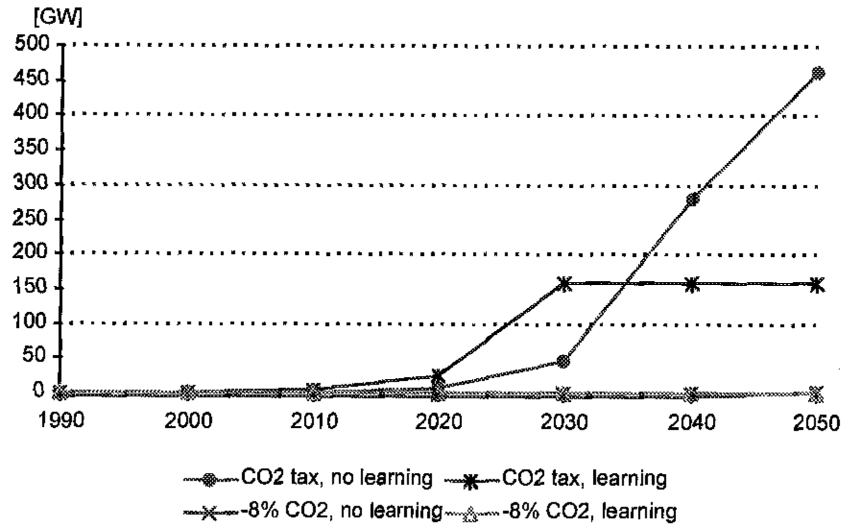


Figure 6.3 *Cumulative capacity solar PV without ('no learning') and with ('learning') endogenous learning*

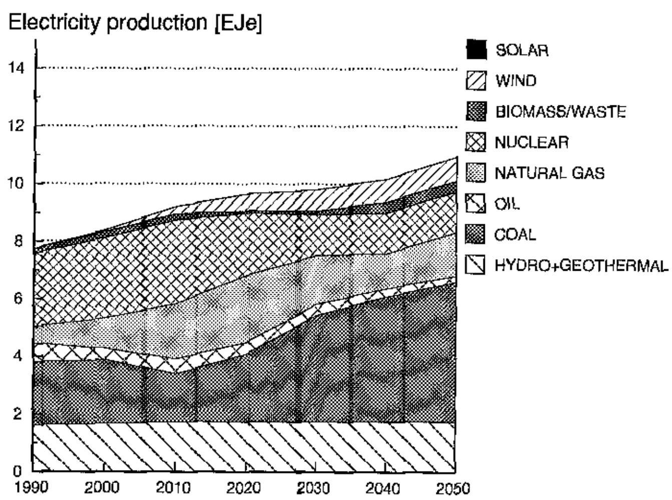


Figure 6.4a *Electricity production: 'Base, no learning'*

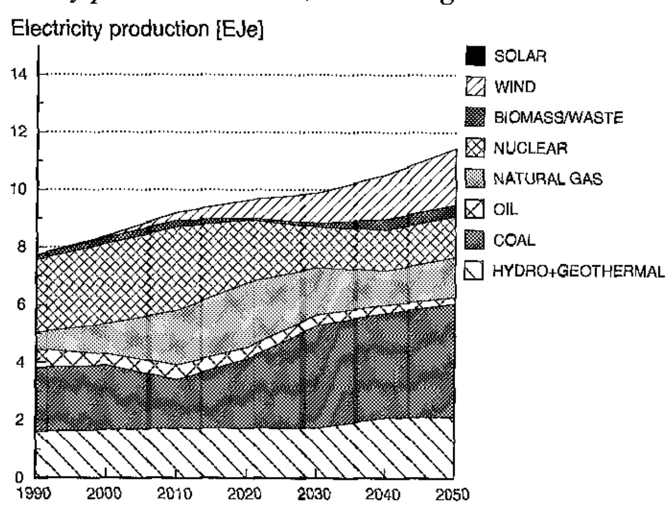


Figure 6.4b *Electricity production: 'Base, learning'*

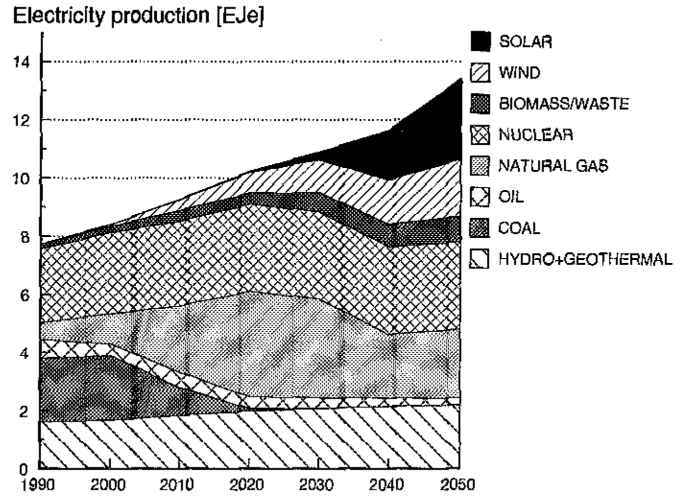


Figure 6.4c *Electricity production: 'CO$_2$ tax, no learning'*

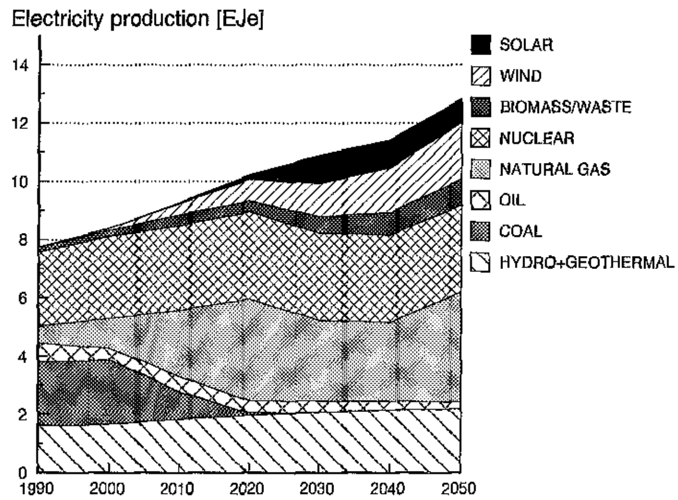


Figure 6.4d *Electricity production: 'CO$_2$ tax, learning'*

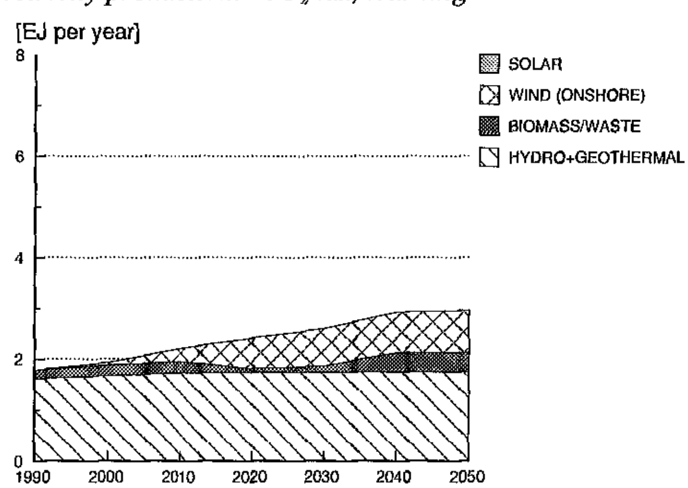


Figure 6.5a *Electricity production from renewables: 'Base, no learning'*

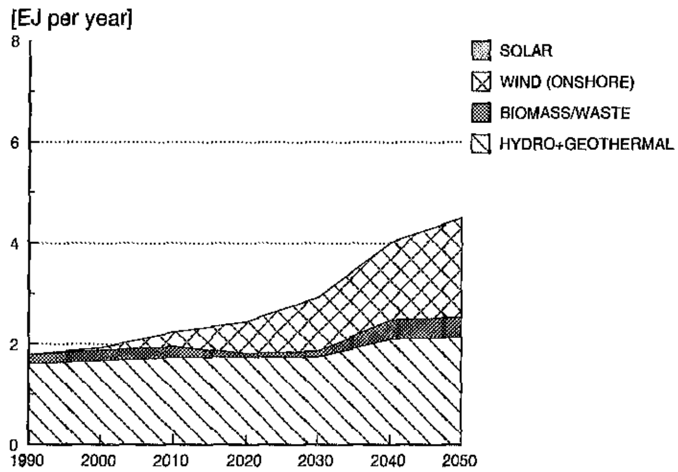


Figure 6.5b *Electricity production from renewables: 'Base, learning'*

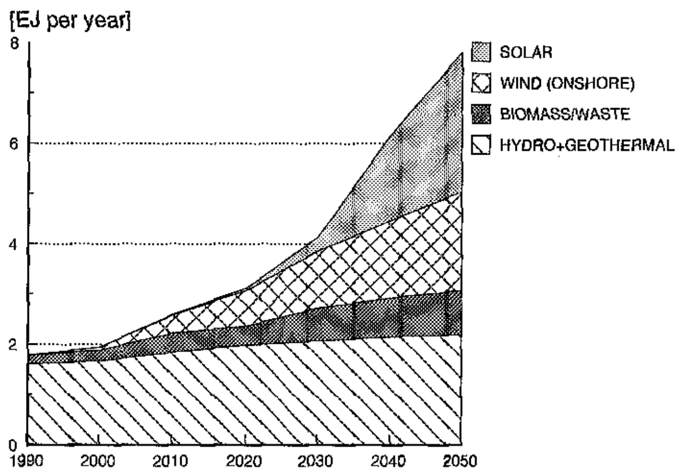


Figure 6.5c *Electricity production from renewables: 'CO_2 tax, no learning'*

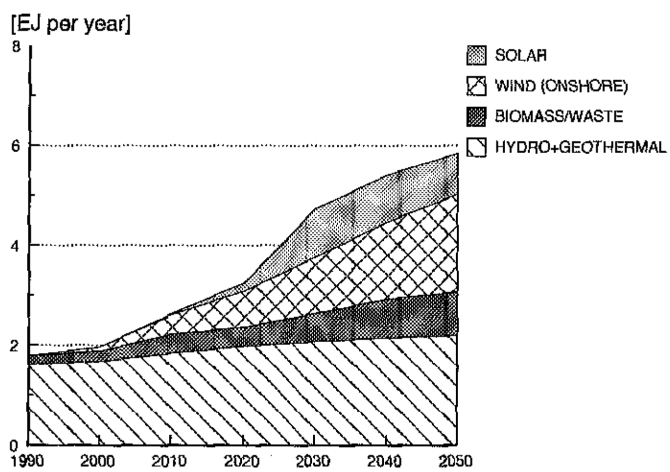


Figure 6.5d *Electricity production from renewables: 'CO_2 tax, no learning'*

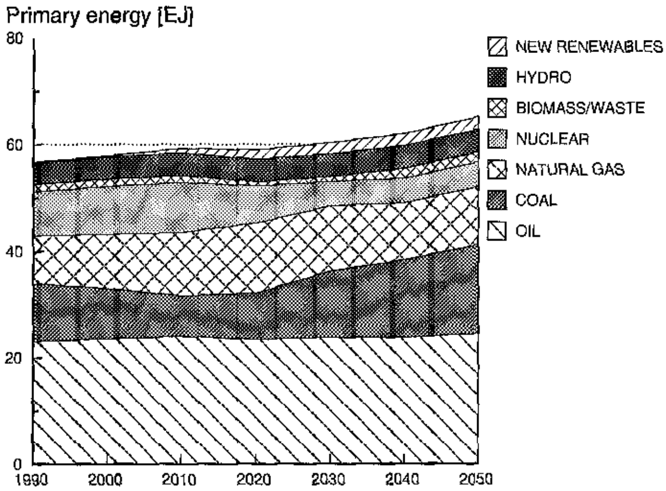


Figure 6.6a *Primary energy mix: 'Base, no learning'*

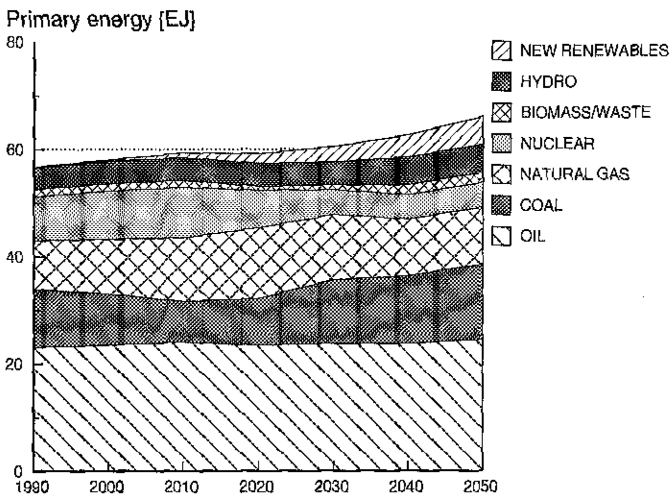


Figure 6.6b *Primary energy mix: 'Base, learning'*

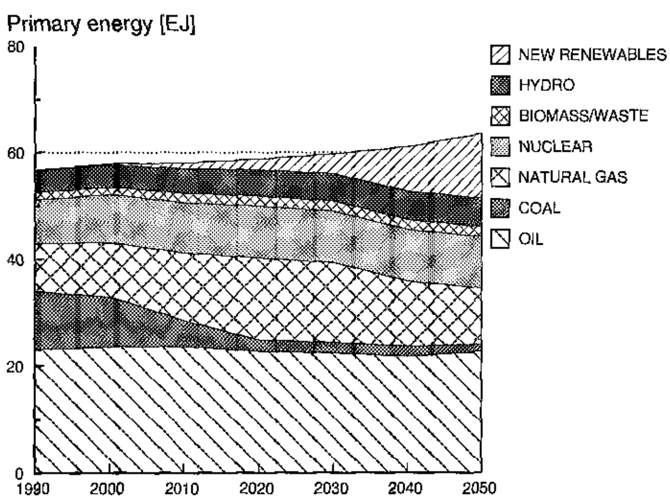


Figure 6.6c *Primary energy mix: 'CO_2 tax, no learning'*

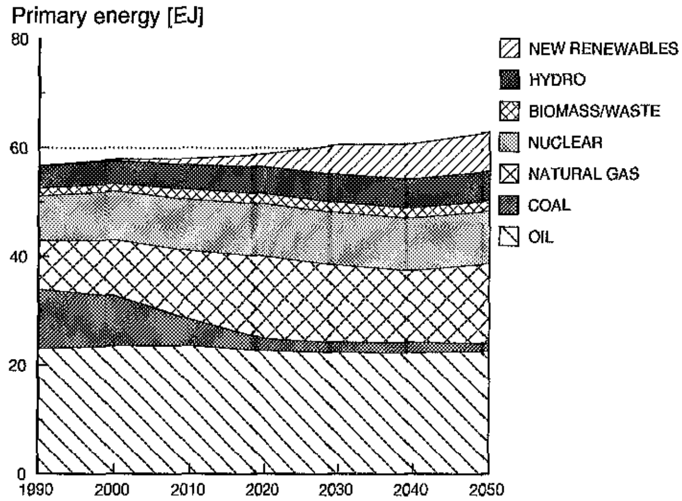


Figure 6.6d *Primary energy mix: 'CO_2 tax, learning'*

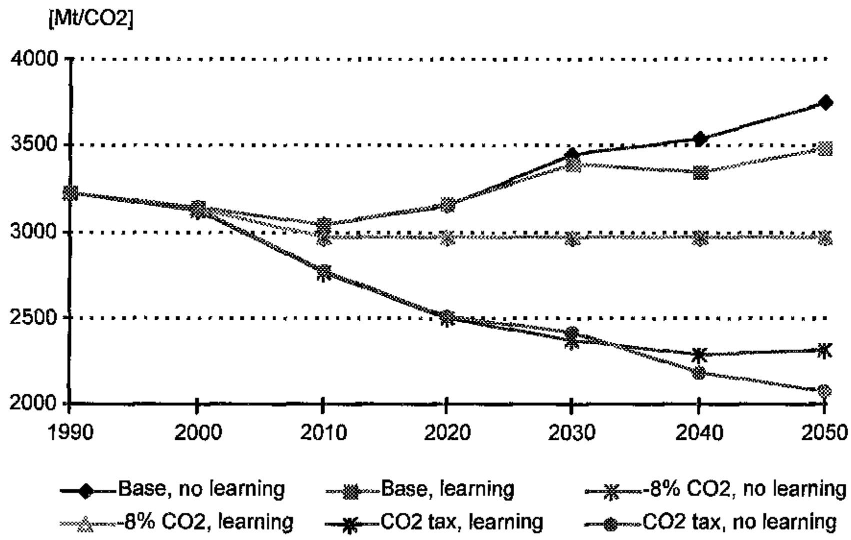


Figure 6.7 *CO_2 emissions in base cases and CO_2 policy variants*

Despite less cumulative capacity in the 'CO_2 tax, learning' case compared to the 'CO_2 tax, no learning' case, the specific investment cost for solar PV becomes lower than in the 'CO_2 tax, no learning' case which follows the exogenous path of the 'Base, no learning' case, see Figure 6.8. Note that already for the year 2000, the cost in the 'CO_2 tax, learning' case drops to about 3400 ECU/kW, a value not really realistic given today's knowledge. In the '-8% CO_2, no learning' case, solar PV is not employed at the cost remains at the initial level. This may indicate that the original exogenous investment cost projection is not consistent with the concept of 'learning by doing'. Also, the 'actual' progress ratio calculated from the model result of the 'CO_2 tax, no learning' case amounts to 0.85, somewhat above the progress ratio used for the 'learning' case (0.81).

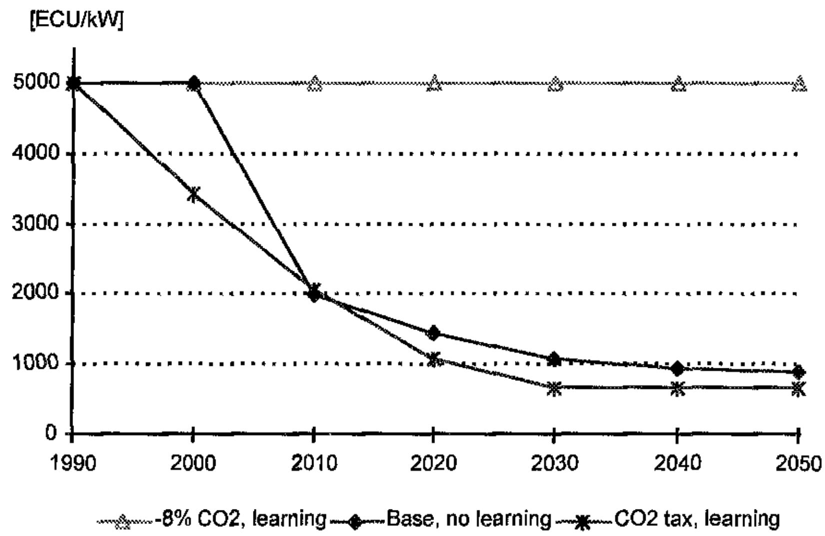


Figure 6.8 *Specific investment cost solar PV: original exogenous projection ('Base, no learning') and two endogenous results for two learning cases*

6.3 R, D&D cases

Adopting the concept of endogenous learning, several R,D&D interventions can be considered that aim to speed up the market penetration of new technologies. Three types of R,D&D variants have been defined, each with the potential to lower the technology investment cost, such that the technology can become cost-effective within the time horizon of the model. More background on these cases has been given in Section 5.3.

6.3.1 R&D leading to lower initial investment cost

Fuel cell car

The first R, D&D case entails a reduction in the initial investment cost SC_0 of the fuel cell (FC) car, from 10745 to 8000 ECU/GJyr (equivalent to 78550 to 58500 ECU/veh, respectively). This still does not make the FC car cost-effective in the base case. In combination with CO_2 policy, the FC car enters the solution and capacity is installed up to its predefined maximum cumulative capacity in, see Figure 6.9 for the '-8% CO_2, learning' cases. The maximum cumulative capacity value of 1030 PJ/yr appears to be too low. This is a similar behaviour as for solar PV in the 'CO_2 tax, learning' case (see Figure 6.3, Section 6.2). Section 6.4 presents also results with an increased value of 3000 PJ/yr.

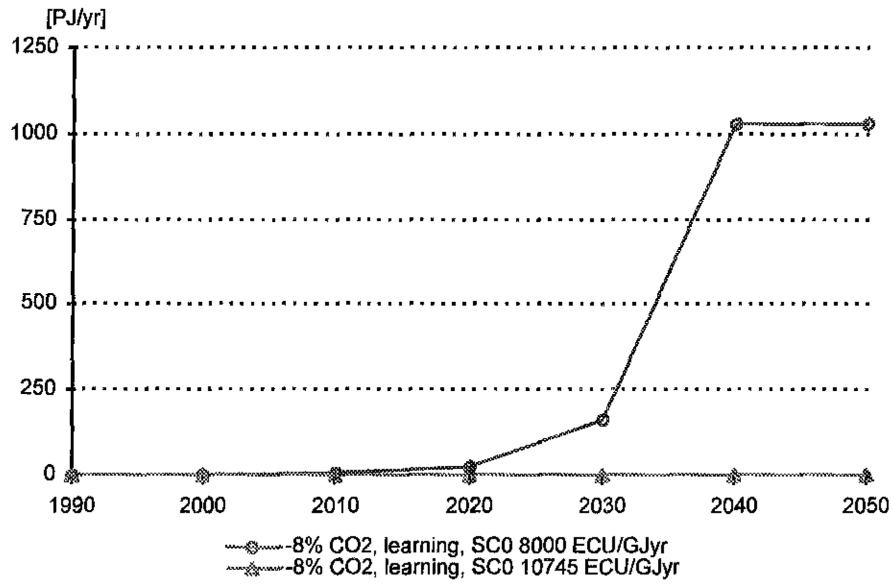


Figure 6.9 *Cumulative capacity FC car with SC_0 10745 and 8000 ECU/GJyr (equivalent to 78550 and SC_0 58500 ECU/veh, respectively)*

In case the FC car enters the solution with endogenous learning (with SC_0 equal to 8000 ECU/GJyr), the specific investment cost is below the level of the original (LP) '-8% CO_2, no learning' case (without endogenous learning but with exogenously specified cost), see Figure 6.10. The two cost curves are similarly shaped. However, in the '-8% CO_2, no learning' case, the FC car is not introduced and the exogenous cost projection is therefore not consistent with the concept of learning by doing. The '-8% CO_2, learning' case provides a more consistent result.

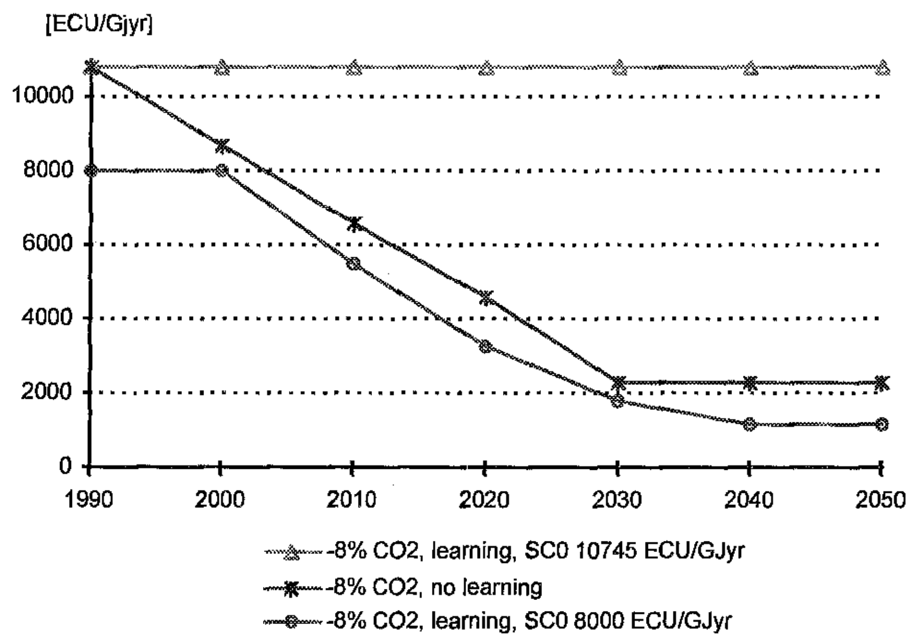


Figure 6.10 *Specific investment cost FC car with SC_0 equal to 10745 and 8000 ECU/GJyr (equivalent to 78550 and SC_0 58500 ECU/veh, respectively)*

Cost-benefit analysis. The overall discounted energy system costs (net present value) can be used to calculate the benefit of reducing the initial specific investment cost. This benefit equals the difference between the two corresponding '-8% CO2, learning' cases and amounts to 1435 MECU. This amount can be seen as the benefits from the initial cost reduction, or the returns to the R&D expenditure needed. This provides an order of magnitude for the R&D cost to be spend at most to achieve the initial cost reduction of 25%.

Initial cost reduction solar PV

Even with an initial cost reduction from 5500 ECU/kW to 3000 ECU/kW (which is considered very low), solar PV does neither become cost-effective in the 'Base, learning' case nor in the '-8% CO_2, learning' case. The only way seems to be to 'believe' in a better progress ratio (than 0.81) or to assume a larger learning potential by increasing the maximum cumulative capacity ($C_{k,\ max}$), now set at 160 GW for the period 2000-2050. The last R, D&D case reported in this section reports varints to the 'Base, learning' case with three more favourable progress ratios (0.78, 0.75, 0.72).

6.3.2 Demonstration projects and market stimulation

As an illustration of the role that demonstration projects or market stimulation policies can play, the capacity of solar PV has been set to lower bounds in the early time periods (2000-2020) in an attempt to make it cost-effective thereafter. Three different schemes have been tested, as outlined below. The schemes could also be seen as CO_2 policy measures aimed at stimulating CO_2 free options like solar power. All of these schemes are not sufficient to get solar PV into the solution at higher levels than the specified lower bounds.

Table 6.3 *R&D cases solar PV; lower bounds set on capacity*

Case	2000	2010	2020
1-4	1	4	
1-5-10	1	5	10
1-5-20	1	5	20

Note: the 'CO_2 tax, learning' case with solar PV as cost-effective option had solution levels of 0.5, 4.0, 25.6 GW in these periods.

An other way for market stimulation is to subsidise the technology temporarily, but this type of stimulation measure has not been investigated in the runs reported here.

6.3.3 R&D leading to more favourable progress ratios

IIASA uses a progress ratio of 0.72 for solar PV (Messner, 1997). As outlined in Section 4.3, ECN considers this value rather optimistic and argues a value of 0.81 would be more in line with observed trends, while it will probably become even higher in the future (note: (Mattsson, 1997) reports a value of 0.82).

Despite of this, three variants for the base case have been defined with lowered progress ratios for solar PV: 0.72, 0.75, and 0.78. With 0.72 and 0.75, solar PV enters the solution. Figure 6.11 shows the resulting decrease in specific investment cost. In 2030, a level of about 200 to 300 ECU/kW is reached for a progress ratio of 0.72 and 0.75, respectively. If cumulative capacity is allowed to be built above the pre-defined 160 GW, the model would even get at lower costs. With 0.78, solar PV remains still not cost-effective in the absence of CO_2 policies.

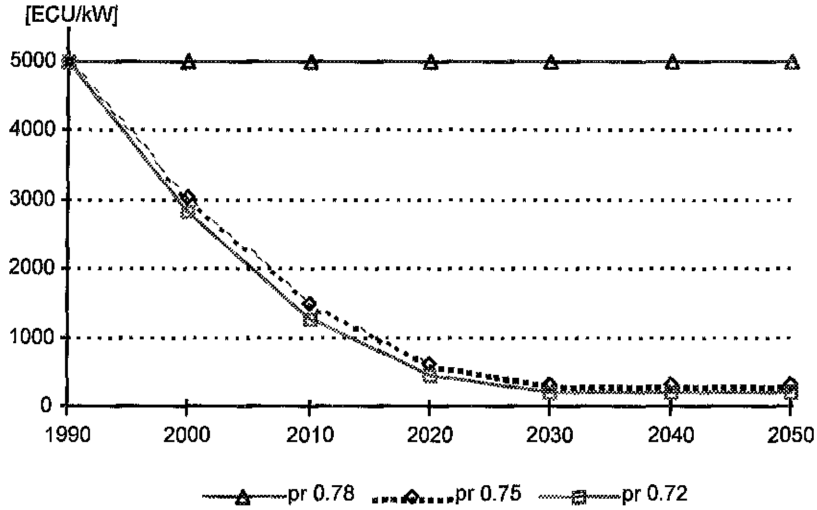


Figure 6.11 *Specific investment cost solar PV with three different lower progress ratios, based on 'Base, learning' case*

6.4 Other sensitivity variants

The previous section has already hightlighted the sensitivity of the model to initial cost and progress ratios. The remainder of the section presents results on other sensitivities. More background has been discussed in Section 5.4.

6.4.1 Learning parameters: initial and maximum cumulative capacity

The FC car has been used to test the sensitivity to these two input parameters. In fact, they determine to a large extent the learning potential of the technology. The two variants comprise a reduction from 0.5 to 0.1 PJ/yr of the initial cumulative capacity and an increase of the maximum cumulative capacity from 1030 to 3000 PJ/yr.

It appears that in both sensitivity variants the FC car becomes cost-effective; with a lower initial cumulative capacity (0.1 PJ/yr) even without CO_2 policy, see Figure 6.12, case 'Base, learning, Ck0 0.1 PJ/yr'. This case also results in the lowest cost path, see Figure 6.13. The maximum cumulative capacity has already been reached in 2030, again an example of setting this value too low (similarly as for solar PV in Section 6.2, Figure 6.3, and in Section 6.3, Figure 6.9 for the FC car). With the maximum cumulative capacity increased from 1030 to 3000 PJ/yr, the FC car becomes cost-effective in the 'CO_2 tax' case (compare 'CO_2 tax, learning' with 'CO_2 tax, learning, Ckmax 3000 PJ/yr' in Figure 6.12).

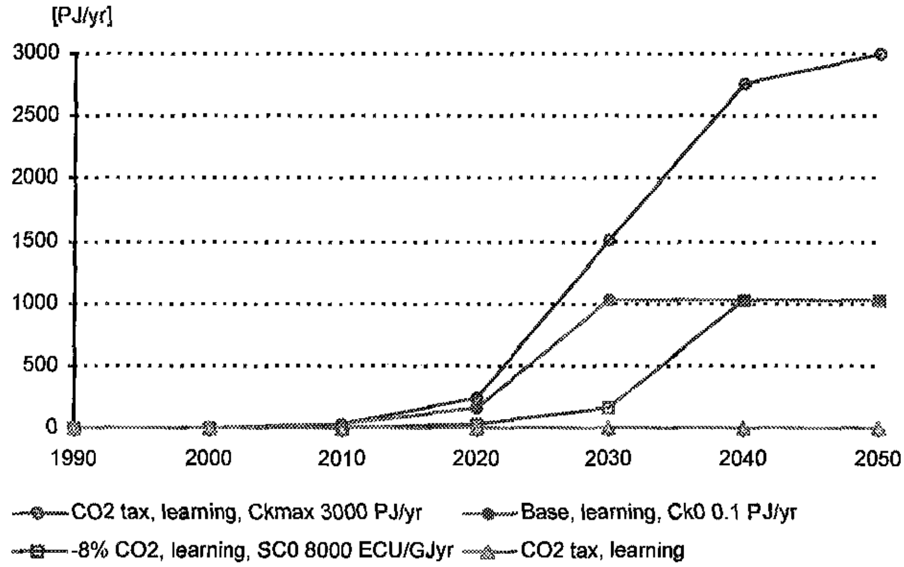


Figure 6.12 *Cumulative capacity FC car with other values for initial and maximum cumulative capacity*
For reference, the 'CO_2 tax, learning' and '-8% CO_2, learning, SC0 8000 ECU/GJyr' cases are displayed too.

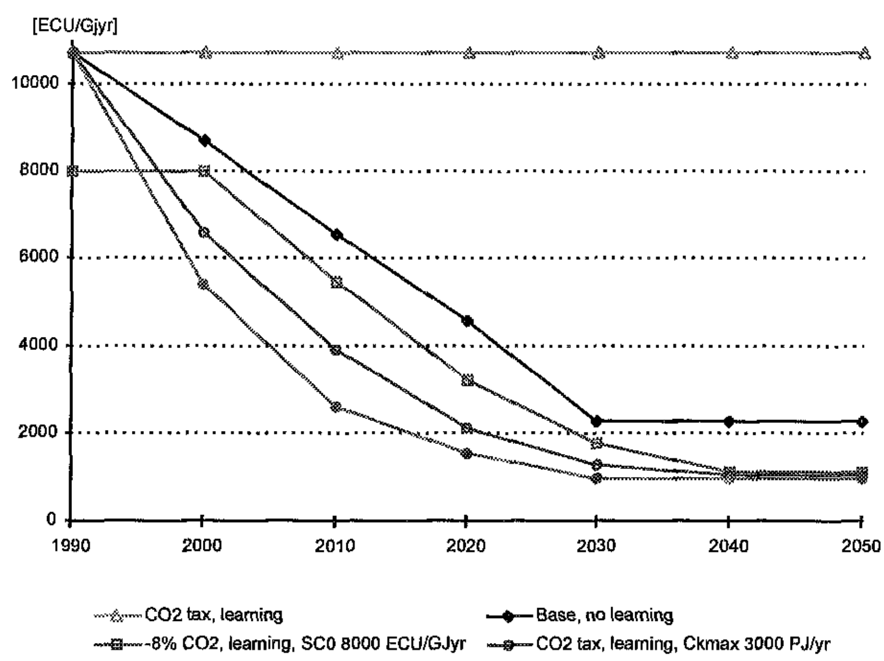
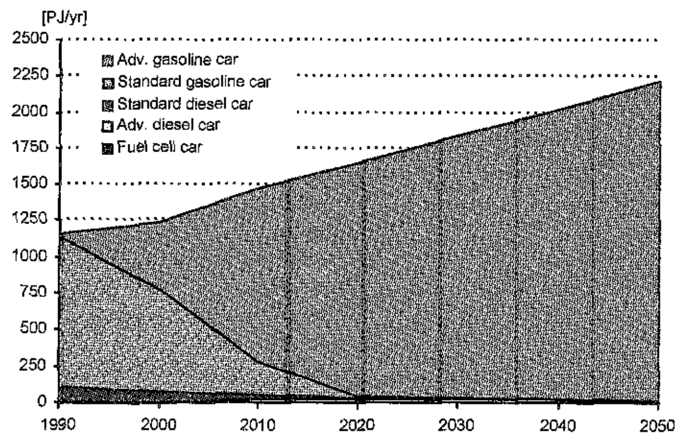


Figure 6.13 *Specific investment cost FC car with with other values for initial and maximum cumulative capacity*
For reference, the 'Base, no learning' and '-8% CO_2, learning, SC0 8000 ECU/GJyr' cases are displayed too.

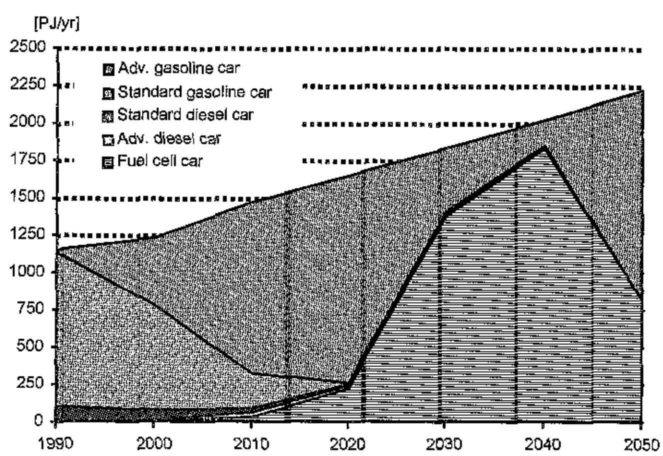
As an example of how endogenous learning can have an impact on the market allocation in a specific end-use demand sector, Figures 6.14 (a) and (b) show the market allocation for the main end-use technologies in the passenger car sector. As can be seen, the FC car takes over a lot of market share of the advanced gasoline car, once it has become cost-effective.

With the original maximum cumulative capacity of 1030 PJ/yr, the FC car does not become cost-effective in the CO_2 cases for both the learning and no learning situation, see Figure 6.14 (a).

The FC car starts to penetrate the market substantially from 2020 on, reaches its maxium in 2040, and, due to the upper bound set on the cumulative capacity, looses market share in 2050, see Figure 6.14 (b).



(a) CO_2 tax, learning and no learning, maximum cumulative capacity 1030 PJ/yr



(b) CO_2 tax, learning, maximum cumulative capacity increased from 1030 to 3000 PJ/yr

Figure 6.14 *Market shares of gasoline/diesel/FC cars in two different cases for initial and maximum cumulative capacity*

6.4.2 Model formulations and accuracy of segmentation

The formulation used is basically the same as reported in (Kypreos & Barreto, 1998b,c,d). The main difference is the use of an alternative segmentation scheme for the cumulative cost curve. PSI has also experimented with an alternative segmentation scheme (Kypreos & Barreto, 1998c; see also Section 2.2.3 of the underlying report). In stead of an equally spaced ('linear') segmentation, ECN also used a segmentation based on a logarithmic division of the cumulative cost curve. Such a scheme results in smaller segments in the region where the cost reduction is significant and in larger segments where the learning effect saturates. So, this 'logarithmic' scheme has a similar effect as the alternative PSI segmentation.

These alternative segmentation schemes seem necessary for learning technologies that are in their very initial phase of development or commercialisation or for technologies that are not even available right now but are expected in the near future.

Another parameter that affects the segmentation is the number of breakpoints used. The larger the number of breakpoints, the better the accuracy with which the cumulative cost curve is estimated. In addition to the default number of breakpoints, 6, runs have been carried out for 10 and 20 breakpoints. Figure 6.15 shows the objective values in these runs, for the linear and logarithm scheme and for three different numbers of segments. The more accurate the segmentation is, which means more segments or the logarithmic segmentation, the larger the objective value is. This shows that the MIP formulation, which inherently underestimates the cost compared to the original non-linear formulation, gets more accurate with an increased number of segments and with the 'logarithmic' segementation scheme. It should be noted that the market penetration in all of these cases did not differ. For these specific cases, this is caused by the fact that all 3 learning technologies are invested in up to their maximum and remain cost-effective even with the changed (higher) investment costs associated with them. For other cases, the market penetration could change as a result of an other segmentation, e.g. as observed in the PSI experiments with the MIP ERIS prototype (Kypreos & Barreto, 1998d).

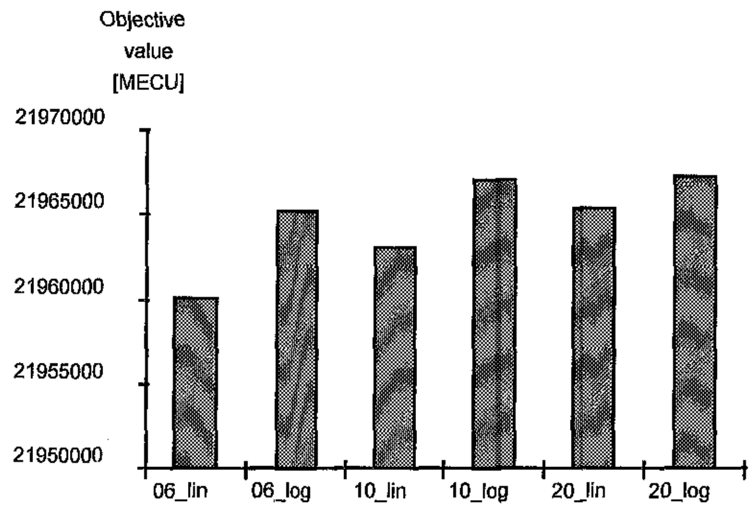


Figure 6.15 *Objective value as function of segmentation, depending of number of segments and of location of breakpoints (CO_2 tax cases)*

The drawback of a more accurate segmentation is an increase in solution time. Figure 6.16 shows the solution times needed in the CO_2 tax cases. As a reference, the corresponding LP (CO_2 tax, no learning) case is given too. The LP case takes 3,5 minutes to solve (using an interior point method; a conventional simplex method would need more). The MIP cases (CO_2 tax cases with learning) need 13 to 55 minutes depending on the accuracy i.e. segmentation. As can be seen, the solution times increase with the number of breakpoints. In addition, the logarithmic segmentation takes more time than a linear segmentation. In practice, it is important to find a good balance between the accuracy of the segmentation and the execution time needed to solve the MIP problem.

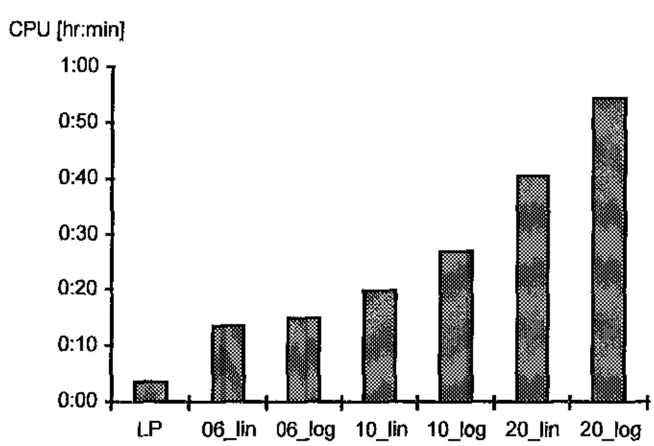


Figure 6.16 *Solution times needed as function of segmentation, depending of number of segments and of location of breakpoints (CO_2 tax cases, learning, MIP) (For reference, the original LP case has been displayed too)*

6.4.3 Number of technologies

The computational complexity of the MIP problem is a limiting factor for the number of learning technologies. Too large a number may encounter excessive solution times or memory requirements. To get an indication of the computational difficulties for the MARKAL-EUROPE model, the number of learning technologies was increased to 5 and 10. Figure 6.17 shows execution times needed to solve these problems and a corresponding problem with 3 learning technologies and the original LP model (0 learning technologies). As can be observed, the solution times increase significantly but remain acceptable. All runs were performed on a Pentium 166 Mhz PC with 64 Mb RAM. Note that solution times may also depend on the input data. The two runs with 10 technologies had only a slight difference in input, but solution times were quite different.

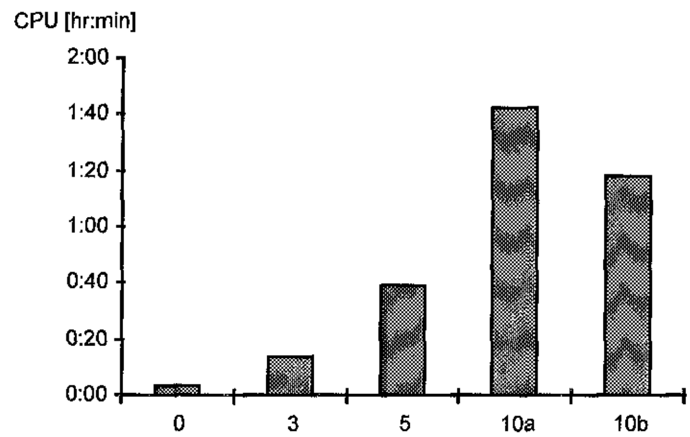


Figure 6.17 *Solution times needed as function of the number of learning technologies (CO_2 tax cases, 0 = LP run, other are MIP runs with learning)*

Given the about 20 key technologies as identified in Chapter 4, the conclusion is that there seems to be no computational bottleneck in solving a large scale MARKAL model of the size of MARKAL-EUROPE with the MIP formulation for endogenous learning.

6.4.4 Discount rate

One sensitivity case with a lower rate, 2% in stead of 5%, showed that in that case solar PV already becomes cost-effective in the moderate CO_2 reduction case (-8% less compared to 1990 level from 2010 on). This illustrates that the use of a different discount rate, in this case a lower value, can make a learning technology more cost-effective, and will have effect on its learning. In particular for scenario studies with a long time horizon, the discount rate could also be interpreted as the 'social rate of time preference' instead of directly related to the investment decision. In the former, more normative approach values of 2-3% seem more appropriate (Lako et al., 1998a).

6.4.5 Solver options

The solver used for the MIP problems is OSL Release 2, version 1.3.055-033 (GAMS, 1998). Two OSL solver options appear to be important for generating optimal solutions efficiently.

The first is the relative optimality criterion 'OPTCR' that should be set small enough to obtain global or nearly global optimal solutions. The default value of 0.1 (means within 10 % of the global solution) is not small enough. A value of 10^{-9} appears to be acceptable for the MARKAL-EUROPE runs reported here: in all cases global optimal solutions were generated. It should be noted that small values for this criterion increases the number of nodes in the MIP Branch & Bound algorithm and hence the solution times and memory requirements. For large scale problems, it may occur that global solutions cannot be generated due to the limited capabilities of the PC used. The energy system analyst then has to be satisfied with non-optimal solutions. The test runs reported here did not have this problem, even for cases with a relatively large number of learning technologies (and hence, a larger number of discrete variables in the MIP problem to solve).

A second, even more important parameter is the 'STRATEGY' parameter that defines the strategy for deciding on the way of branching in the Branch & Bound algorithm. With the default value (STRATEGY=1), the algorithm was unable to generate (optimal) solutions. Even for relatively large values of OPTCR (10^{-3}, 10^{-4}), too many nodes had to be processed and tree information had to be saved, resulting in severe memory requirements beyond the capability of the PC used. With the STRATEGY parameter set to 48, a combination of 16 and 32 using heuristics to compute new pseudo-costs for all variables, optimal solutions were generated efficiently. Experiments were also carried out with STRATEGY=50, adding the '2' strategy. This strategy assumes a valid integer solution has been found before and is beneficial for restarting, e.g. by using the perturbation feature that has been implemented in the ECN MARKAL MIP model.

7. DISCUSSION OF RESULTS

7.1 Insights

The MIP formulation for learning curves as introduced to the energy systems analysis MARKAL model (MMARKAL 2.2. version) generates (global) optimal solutions rather efficiently. Hence, one important aspect of technology learning, the investment cost of an energy technology, can now be calculated endogenously.

Close examination of a large scale MARKAL application, the MARKAL-EUROPE database, indicates that re-evaluation and redefining the reference energy system is instrumental to obtain consistent results. The resources needed for this task should not be underestimated. From the odd 500 technologies in the database, about 20 can be viewed as so-called key technologies with respect to learning.

Collection of the additional input data needed is not a trivial task. Examples are the progress ratios and the ultimate potential of a learning technology (both in terms of capacity that can be installed and the ultimate cost). Significant uncertainties surround the estimates of progress ratios and the initial parameters for learning technologies that are still in an early phase of their life cycle (R&D phase, pre-commercial phase).

Endogenisation of the investment cost is inherently more consistent than the usually applied exogenous cost projections. The experiments show that other MARKAL modelling features like the sensible use of bounds and growth constraints are needed to obtain plausible results. If not treated with care, behaviour may be observed like:
- exponential increase in capacity (starting from scratch to GW's of capacity in a next time period),
- unlikely low costs for learning technologies that are adopted and cost-effective.

The new model is able to evaluate the impact of energy policy instruments through their (anticipated) effects on technology development. The experiments clearly show that CO_2 policy can boost development of renewables. For a more detailed evaluation of the effect of R,D&D policy measures additional modelling work is needed.

The experiments also show that the learning MARKAL model is very sensitive to the following technology data input parameters:
- progress ratio (*pr*)
- initial investment cost (SC_0)
- initial and maximum cumulative capacity.

In particular for technologies that currently have high costs and are only marginally applied (and hence have the largest learning potential), changes in these parameters can have very large consequences. The initial cumulative capacity reflects the start location of the technology on its learning curve and hence, whether the technology is in the phase of fast potential learning (large decrease with additional capacity) or in more mature phases. The assumed maximum cumulative capacity determines the ultimately achievable cost level, but is also one of the determinants for the accuracy of the segmentation (linear approximation) of the cumulative cost curve.

The ratio of the maximum cumulative capacity over the initial cumulative capacity determines the maximum number of doublings (n), and thereby the potential for possible cost reduction (pr^n). The maximum cumulative capacity parameter should be set large enough to prevent undesired, premature saturation effects, but should also reflect a realistic view on the maximum potential of the technology. The resulting lower bound on the investment cost (i.e. $SC_0 \times pr^n$) should be checked to make sure it cannot drop to unrealistically low levels.

On the basis of the MARKAL tests reported here, it does not seem possible to declare any of the learning parameters as being the 'most important'. However, most of the uncertainty seems to be associated with a technology progress ratio.

For technologies that currently have high costs and are only marginally applied, the model tends to install capacity up to the maximum cumulative capacity, as the technology tends to capitalize to the extent possible on the benefits from becoming cheap enough through learning. Under certain conditions this behaviour can be an example of the 'lock-in' effect. In contrast, if it does not start its expansion on the short term, the technology is effectively 'locked-out' for the longer term.

7.2 Limitations

Although the MARKAL model with endogenous technological learning has definitely an added value compared to the conventional model, it is good to be aware of limitations that still exist. The most important limitations are:

- Endogenous learning is restricted to investment cost only, other characteristics like efficiency remain exogenous.
- Inter-dependent learning between classes of technologies that have something in common, e.g. spill-over/cross-over effects between separately modeled technologies, have not yet been dealt with.
- The geographical scale of the MARKAL-EUROPE model does not allow to cover global developments. A full-scale global MARKAL database is not available, although the geographical coverage is increasing by the availability of more and more MARKAL country databases and the possibility to couple these into one regionalized MARKAL model (in the next so-called RMARKAL 3.1 version). For some technologies such a global scale may not always be necessary (e.g. high-efficiency gas boilers for residential space heating in the Netherlands). Others essentially depend on worldwide markets. One possible way to simulate the global scale for these options is to assume multipliers to link e.g. capacity growth in Western Europe with the rest of the world.

relevance of the additional data needed. Even if good data can be extracted from historical trends, It should be noted that also in conventional energy models with exogenously specified costs, the assumed costs and 'implicit' progress ratios play a crucial role in making technologies cost-effective or not. Hence, the availability of accurate data is not only a drawback of the MIP models but inherent to the use of energy system models for scenario studies and technology forecasting studies.

8. CONCLUSIONS AND RECOMMENDATIONS

A full-scale MARKAL model with learning is able to generate globally optimal and consistent solutions efficiently
The experiments with a full-scale MARKAL model database (for Western Europe) show that the new MARKAL MIP model with learning is able to generate globally optimal solutions efficiently. The solution times remain acceptable compared to those of the comparable MARKAL LP model without learning. One important aspect of learning, the specific investment cost of an energy technology, can now be calculated endogenously, which leads to more consistent model outcomes than with the usual exogenous cost projection.

The effects of energy policy instruments on technological development can be evaluated
The new model is suited to evaluate the effect of energy policy instruments. E.g. the impact of CO_2 reduction policy, of demonstration projects and of market stimulation measures on the technological development can be assessed consistently. For an assessment of the effect of R&D policy instruments additional modelling work is needed. The results from another TEEM activity (1.2 Typology and quantification of technology dynamics) should be input to this future modelling work.

Re-evaluation of original reference energy system and technology characterisation needed
For an optimal and consistent use of the benefits of including technology learning, the original reference energy system (RES) and technology characterisations should be re-evaluated. Important RES aspects are: endogenous alignment of technologies, identification of key technologies with respect to learning (about 20 compared to the 500 technologies in the MARKAL-Europe model), and selection of an appropriate level of technological detail. A broad framework has been developed to assess whether observed historical trends can be expected to continue, finally resulting in an assessment of progress ratios to be used for future periods in the model.

Results are sensitive to learning parameter input data
Sensitivity cases have shown the decisive impact of assumed learning parameters (progress ratio, initial investment cost, and initial and maximum cumulative capacity of a technology expected to learn endogenously). In particular for technologies that currently have high costs and are only marginally applied (but which have a large learning potential), the sensitivity of model results to these parameters is very large. These parameters require careful fine-tuning. Moreover, a well-targeted use of bounds and growth parameters is needed to prevent clearly unrealistic results.

Limitations require further modelling improvements
Although the new model feature is a clear improvement, limitations remain in the current model formulation that require additional modelling and technology characterisation

work. The most important limitations are: (a) technologies containing the same key technology still learn independently; (b) uncertainties in combination with learning cannot be taken into account; (c) the geographical scale is limited to Western Europe; (d) quantitative relationships between R&D policy and learning data parameters (e.g. progress ratios, initial cost) are still unknown; and (e) only the specific investment cost learns endogenously (not other parameters like efficiency, capacity utilization etc.).

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ABBREVIATIONS

B&B	Branch and Bound: technique to solve Mixed Integer Programming optimisation models
EC	European Commission
ECN	Energieonderzoek Centrum Nederland (Netherlands Energy Research Foundation)
ECOSIM	Private company on studies on Energy Modelling and Policy Analysis (of IEPE, UK)
EIA	Energy Information Administration (USA)
ESD	Private company on studies on Energy Modelling and Renewables (UK)
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
FC	Fuel Cell
FCC	Fuel Cell Car
GAMS	General Algebraic Modelling System, language in which the MARKAL model is coded
GENIE	Global Energy systems model with Internalized Experience curves, gloabl model developed at Chalmers University
ICCS	Institute on Economy, Energy and Environment Modelling of NTUA
IEA	International Energy Agency of the OECD
IEPE	Institut d'Economy et de Politique de l'Energie (France)
IIASA	International Insititute for Applied Systems Analysis (Austria)
KUL	Katholieke Universiteit Leuven (Catholic University of Leuven, Belgium)
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
NEMS	National Energy Modelling System
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, provided with the GAMS software
POLES	Prospective Outlook on Long-term Energy Stategy, global energy model developed for the EC
PRIMES	EU energy systems model, developed for the EC
PSI	Paul Scherrer Institute
RTD	Research and Technology Development
TCH	Technology

ANNEX A GROWTH FACTORS, INVESTMENT BOUNDS, AND MAXIMUM CUMULATIVE CAPACITY

It should be noted that a combination of investment or capacity bounds in MARKAL is often used to model a more realistic penetration of new technologies e.g. following an S-curve type of pattern. Growth parameters can be used to model the first phase of the increase in capacity and to prevent an almost unlimited growth in capacity once a technology becomes cost-effective. In addition, investment bounds in the later time periods can be used to prevent a technology from penetrating unlimitedly or for modelling saturation effects. Of course, these modelling features should be used carefully

Figure A.1 shows the solar PV potential, expressed as the maximum cumulative capacity that can be achieved until and including 2070 (9 periods). The maxima are based on the assumed learning parameters and additional growth parameters and investments bounds.

As can be seen, the maximum annual growth parameter (gr, 1.2 in this case) determines the potential in the first three periods (period 1-3: 1990-2010). In combination with the maximum cumulative capacity (ccap_max), the potential is further bounded in the next two periods (4-5: 2020-2030, shown in the line 'ccap_ini+gr+ccap_max'). This is the pattern that emerged from the 'CO_2 tax, learning' case (see Figure 6.3). Adding an annual investment bound (ibondup, 40 GW in this case) leads to a linearly increasing potential in the periods 2020-2040 (4-6). Adding again the ccap_max bound, this linear trend is bend down for the last period.

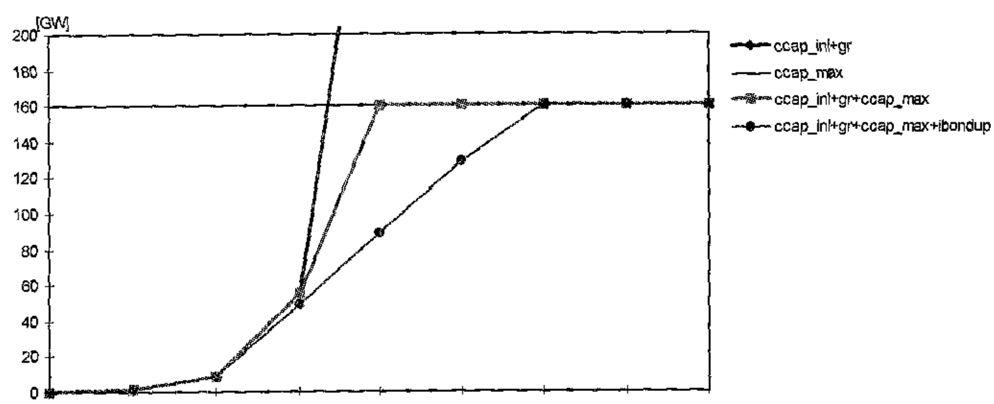

Figure A.1 *Maximum cumulative capacity for solar PV in Western Europe depending on assumed learning parameters and other bounds*