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# ENHANCEMENTS OF ENDOGENOUS TECHNOLOGY LEARNING IN THE WESTERN EUROPEAN MARKAL MODEL

## Contributions to the EU SAPIENT project

M.A.P.C. de Feber
G.J. Schaeffer
A.J. Seebregts
K.E.L. Smekens

## Preface

This report summarises the ECN contributions to the EU SAPIENT project. The ECN contributions to this project have been carried out on behalf of the European Union, DG RES (under the 5th Framework Programme), contract ENG2-CTI999-00003. It has been co-sponsored by ECN's own funds that come from the Dutch Ministry of Economic Affairs. The project is registered at ECN under project number 77261. A previous draft (dated March 2002) of this report ECN-C--03-032 had the report number ECN-C--02-023 that is no longer valid.

## Acknowledgement

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## Abstract

The primary topic of the SAPIENT project and its predecessor TEEM has been the issue of incorporating technology learning endogenously in energy models and trying to determine the impact of public R&D on this learning process. ECN has incorporated the learning mechanism into the MARKAL model using an extended database for the Western Europe energy system. By using advanced modelling techniques (Mixed Integer Programming) and the concepts of key components and technology clusters more than 60 technologies in the power sector have been endowed with learning characteristics. By this approach solving times could be kept within a reasonable length, i.e. less than 20 minutes per run.

An important insight gained from model runs with many learning technologies, including conventional technologies, is that new technologies aiming to 'beat' conventional ones are aiming at a 'moving target'. Also conventional technologies can learn, and this aspect makes it much more difficult for new sustainable technologies to penetrate the market in the model.

By using a Monte Carlo approach uncertainties in important learning parameters could be analysed. It appeared for instance that the main factor that determines the uncertainty on floor costs for photovoltaic (PV) energy production is the uncertainty in the PV progress ratio.

One of the main targets of the SAPIENT project was to find ways to model the effect of R&D on technology learning. ECN has explored an approach to capture this effect by assuming a relationship between the R&D-intensity of a technology and its progress ratio. Following this approach it was found that uncertainties in the overall progress ratio are often higher than the effect additional R&D can have on a certain technology. Also, model outcomes depended rather on the carbon prices used in the scenarios than on the enhancement of learning by R&D. This suggests that a stimulus for sustainable technologies cannot be reached by R&D-measures alone.

However, much more research work will have to done on how to model the relation between R&D-expenditures and cost reduction. Although the R&D-intensity approach circumvents several of the pitfalls of the two-factor learning curve used by the other partners in the project, it is still far from perfect and based on several assumptions which need to be studied with more scientific scrutiny.

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# 1. INTRODUCTION

Technology learning, or technology change, is widely recognised as a key factor in economic progress, as it enhances the productivity of factor inputs. In recent years also the notion has developed that targeted technological development is a main means to reconcile economic ambitions with ecological considerations (e.g. Grübler, 1998). This raises the issue that assessments of future trajectories of, for example, energy systems should take into account context-specific technological progress. Rather than taking characteristics of existing and emerging technologies as a given, their development should be a function of dedicated Research, Development and Demonstration (RD&D) actions and market deployment under varying external conditions.

In recent years, endogenous technological learning (ETL) has shown to be a very promising new feature in energy system models (e.g. MARKAL). A learning curve is implemented describing the specific (investment) cost as a function of the cumulative capacity for a given technology. It reflects the fact that technology costs often decline as a result of its increasing adoption into the society due to the accumulation of knowledge (e.g. due to learning by doing mechanism).

In 1998, ECN carried out the first MARKAL experiments with ETL in the framework of the EU[1] sponsored TEEM project (Energy Technology Dynamics and Advanced Energy System Modeling). At that time, the concept of 'clusters of technologies' was first introduced (Seebregts et al., 1999 and 2000). The 'cluster approach' was also used in the successor of this project, called SAPIENT (Systems Analysis for Progress and Innovation in Energy Technologies) which started in Spring 2000. This concept, which is needed to deal with interdependent learning between technologies, has been dealt with in more detail in the recent ECN SAPIENT experiments that followed on the TEEM experiments. During this project the number of clusters has been extended, as will be outlined in Chapter 5.

This report summarises the ECN contributions to the SAPIENT project, which were carried out on behalf of the European Union and co-sponsored by ECN's own funds that come from the Dutch Ministry of Economic Affairs[2]. In the earlier TEEM project learning curves were implemented in the various energy system models involved. The main focus was on the learning by doing mechanism (i.e. the technological progress achieved by increasing the total capacity installed). In the SAPIENT project, efforts have been made to also include the technological progress caused by dedicated (public) R&D. If the two mechanisms are combined in one curve a so-called 'two factor learning curve' (2FLC) results.

The structure of this report is as follows. Chapter 2 describes ECN's (indirect) approach to analyse two factor learning curves with the MARKAL Western European model. The implementation of this approach in MARKAL is outlined in Chapter 3. Chapter 4 describes the used of Monte Carlo Analysis (MCA) with the MARKAL model. MCA can give an indication of the parameter and data uncertainties within a particular scenario. Chapter 5 presents the model run results, preceded by a short overview of the assumptions on technology data and scenarios. Chapter 6 ends with the formulation of the conclusions and recommendations. Annex A to Annex C contain supporting information, while a special Annex D is devoted on a model technology data comparison for the models PRIMES, POLES, MARKAL, MESSAGE, ERIS, and MERGE-ETL, a separate task within the SAPIENT project.

[1] The European Commission is acknowledged for sponsoring the ECN contribution to the TEEM project (Non Nuclear Energy Programme JOULE III, contract JOS3-CT 0013).

[2] The European Commission and the Dutch Ministry of Economic Affairs are acknowledged for sponsoring the ECN contributions to the SAPIENT project ($5^{th}$ Framework Programme, contract ENG2-CT1999-00003 and ECN project number 77261).

# 2. IMPACTS OF R&D INTENSITY ON PROGRESS RATIOS IN MARKAL

## 2.1 Reasons to stick to one-factor learning curves

In this chapter an indirect approach is described to analyse two-factor learning curves (2FLC's) with the MARKAL application for Western Europe. There were several reasons to refrain from introducing 2FLC directly in MARKAL:

*Statistical fit of one-factor versus two-factor learning curves*

The TEEM project (TEEM, 1999) has shown that 2FLC does not always results in a better fit to the data than the single factor learning curve (1FLC: learning by doing and learning by searching incorporated in one factor). So, a fundamental data problem existed to provide statistical support for such a two-factor approach. These empirical flaws are not surprising, since a firm theoretical basis to support the relationship with two factors does not yet exist.

In other recent literature, attempts have been described to differentiate between these two factors in fitting an experience curve, e.g. (Kouvaritakis et al., 2000; Klaassen et al., 2002 and Mikita and Schrattenholzer, 2002).

The learning curve then looks like (adapted from (Kouvaritakis et al., 2000):

$$Ct = C0 \times (CCt/CC0)^{\alpha} \times (CRDt/CRD0)^{\beta}$$

With

| | |
|---|---|
| Ct | unit capital cost at time t |
| CCt | cumulative installed capacity at time t |
| CC0 | cumulative installed capacity at time 0 (base year) |
| CRDt | cumulative R&D effort at time t |
| CRD0 | cumulative R&D effort at time 0 (base year) |
| C0 | unit capital cost at time 0 (base year) |

$\alpha$ and $\beta$ are learning by doing and learning by searching elasticities, respectively. From these the two PRs can be calculated.

The equation given above can be fitted by first converting it to the form:

$$\text{Log}(C) = a \times \log(CCAP) + b \times \log(CRD) + c$$

Both (Kouvaritakis et al., 2000) and (Mikita and Schrattenholzer, 2002) found instability in the estimates of the learning parameters (based on ordinary least squares), possibly due to multicollinearity. Previous estimates by IPTS in the TEEM project (TEEM, 1999) showed that fitting the one-factor learning curve (1FLC) produced values for $R^2$ that were far better than obtained with fitting the two-factor learning curve (2FLC).

*No relatively simple MIP approximation for a complex and technology rich models*

Addition of a 'learning by searching' factor to the current 'learning by doing' learning curve leads to a non-linear programming (NLP) optimisation model that cannot be approximated well by a mixed-integer programming (MIP) model, in case of endogenous R&D shocks. The NLP formulation can only be solved well for only a few technologies (e.g. see Mikita and Schrattenholzer, 2002). Given the complexity of the Western European MARKAL application, in terms of number of technologies (hundreds), and the need to further expand on the concept of clusters of technologies (Seebregts et al., 2000), an NLP formulation would further hamper such expansion: the model would become too complex to be solved.

*Data uncertainty*
The uncertainty introduced by the use of either a 1FLC or 2FLC may be smaller than the uncertainty caused by the value of the 1FLC progress ratio. As illustrated in e.g (Kram et al., 2000, Table 2; McDonald and Schrattenholzer, 2000; and Junginger, 2000), progress ratios for one particular technology exhibit a large uncertainty range, e.g. see the Table for solar PV modules and wind turbines progress ratios in Section 4.4.1. So, methodological uncertainty may be overshadowed by pure data uncertainty. In Section 4, this has been illustrated to some extent for wind turbines).

Therefore, the MARKAL model with endogenous learning was not extended with two-factor learning curves (2FLC's).

## 2.2 Indirect approach to two factor learning curves

As an alternative, ECN proposed to treat the impact of public energy R&D indirectly, that is external to the MARKAL model, and estimates the impact on the progress ratio of the 1FLC. To start with, the basic assumptions behind the approach are:

- Public R&D expenditure is a good indicator for the overall R&D-expenditure.
- Additional R&D budget (an '*R&D shock*') will lead to an increase in the so-called *R&D intensity* of the technology. R&D intensity is defined as the relationship between public R&D expenditures over a period and the turnover of that technology: R&D intensity = (amount of R&D)/(amount of R&D + turnover).
- The higher the R&D intensity, the better the progress ratio.
- This relationship between a change in R&D-intensity and the change in progress ratio is the same for each technology.
- R&D budget for each technology is applied with the same level of efficiency.
- The progress ratio will not change after the period of additional R&D shock.

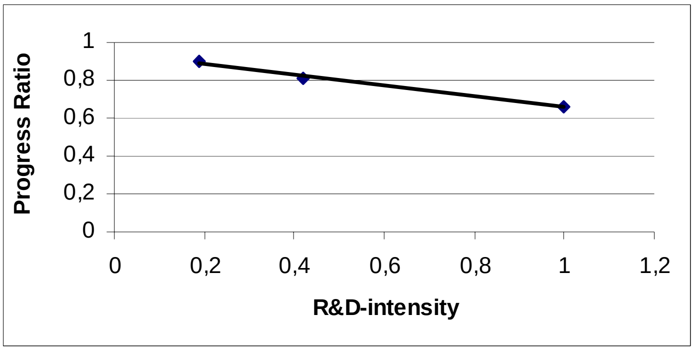
The approach is then as follows:

- The MARKAL model uses the 'overall' progress ratio that includes all factors of learning, including effects of R&D.
- Additional R&D budget (an '*R&D shock*') will lead to an increase in the R&D intensity of the technology.
- An increased R&D intensity will lead to a lower (= better) progress ratio.
- This updated progress ratio is used in the MARKAL model to study the overall impact of R&D.

The quantitative relationship between R&D intensity and the change in progress ratio has been based on available statistics/data for three technologies. In the following table the progress ratios are more or less realistic, and the R&D intensities have been based on SAPIENT data collected by IEPE (Criqui, 2001).

Table 2.1 *Relationship progress ratio vs. R&D intensity for 3 emerging technologies*

| Technology | Progress ratio see (Kram et al., 2000, Table 2, MARKAL-Europe) | Public R&D-intensity 1985-1995 (based on SAPIENT data Criqui) |
|---|---|---|
| Fuel Cell | 0.66 | 100% |
| Solar PV | 0.82 | 42% |
| Wind Turbine | 0.9 | 19% |




PR = -0.29 × R&D-intensity + 0.9451 ($R^2 = 0.9898$)

Figure 2.1 *Fitted relationship progress ratio vs. R&D intensity for 3 emerging technologies*

The figure above indicates that the R&D-intensity elasticity for learning is equal to 0.29% lower (=better) progress ratio for each additional R&D-intensity %point. It also indicates that if no public R&D were spent on a new energy technology, there is still a progress ratio of about 94.5%. This progress ratio is then purely due to non-R&D-factors (i.e. 'learning-by-doing').
The relationship and the resulting coefficients could be further underpinned or estimated on available R&D statistics and PRs of more than these 3 technologies. Based on the relationships outlined above, the procedure to is as follows:

- Estimate the current progress ratio ($PR_{C1}$) of technology $T_1$ without *extra* R&D over a given historical period $P_1$.
- Estimate the R&D-intensity of this technology $T_1$ over the same historical period $P_1$.
- Calculate what would be the amount of R&D to be spent in a reference scenario, assuming that the R&D-intensity stays constant over time.
- Calculate what an *extra* R&D budget of x billion Euro means for the change in R&D-intensity ($\Delta RD_I$).
- Multiply $\Delta RD_I$ by 0.29: This gives the change in PR, $\Delta PR$.
- Add $\Delta PR$ to $PR_{C1}$, resulting in $PR_{enh\text{-}R\&D\text{-}1}$, the new PR, enhanced by additional R&D.

## 2.3 Estimates to be made for key technologies in MARKAL

During the procedure outlined in Section 2.2, several estimates have to be made based on historical data for the key technologies in MARKAL. These include:

- Estimate of the historical progress ratio of the key technology. This includes an estimate of the sales volume and cost reductions of the key technologies over time.
- Estimate of the historical R&D-intensity of the key technology.
- Estimate of future R&D-spending in a reference scenario. This includes an estimate of future sales in the reference scenario.

For these estimates the Technology Improvement Database as developed within the SAPIENT project has been used. Since this database is based on the POLES categorisation of technologies, it had to be related to MARKAL key technologies by 'allocation' factors. These factors can be seen in Table 2.2 (for R&D) and Table 2.3 (for sales).

Table 2.2 *Translation from POLES R&D expenditure figures to MARKAL key technology R&D expenditure figures*

| | Key technologies in MARKAL | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POLES Techn. | NUK | HYK | GTK | FCK | EWK | ESK | BOK | GFK | COK | CCK | STK | Sum |
| HYD | | 1 | | | | | | | | | | 1 |
| NUC | 1 | | | | | | | | | | | 1 |
| NND | 1 | | | | | | | | | | | 1 |
| LCT | | | | | | | 0.5 | | | | 0.5 | 1 |
| CCT | | | | | | | 0.5 | | | | 0.5 | 1 |
| ICG | | | 0.2 | | | | | 0.6 | | 0.1 | 0.1 | 1 |
| OCT | | | | | | | 0.4 | | | | 0.6 | 1 |
| OGT | | | 0.3 | | | | | 0.5 | | 0.1 | 0.1 | 1 |
| GCT | | | 1 | | | | | | | | | 1 |
| GGC | | | 0.8 | | | | | | | 0.1 | 0.1 | 1 |
| CHP | | | 0.7 | | | | | | | | 0.3 | 1 |
| SHY | | 1 | | | | | | | | | | 1 |
| WND | | | | | 1 | | | | | | | 1 |
| DPV | | | | | | 1 | | | | | | 1 |
| BGT | | | 0.2 | | | | | 0.6 | | 0.1 | 0.1 | 1 |
| RPV | | | | | | 1 | | | | | | 1 |
| BF2 | | | | | | | | 0.4 | | | 0.6 | 1 |
| FCV | | | | 1 | | | | | | | | 1 |
| SFC | | | | 1 | | | | | | | | 1 |
| MFC | | | | 1 | | | | | | | | 1 |

Table 2.3 *Translation from POLES sales figures to MARKAL key technology sales figures*

| | Key technologies in MARKAL | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| POLES Techn. | NUK | HYK | GTK | FCK | EWK | ESK | BOK | GFK | COK | CCK | STK | Sum |
| HYD | | 1 | | | | | | | | | | 1 |
| NUC | 1 | | | | | | | | | | | 1 |
| NND | 1 | | | | | | | | | | | 1 |
| LCT | | | | | | | 0.60 | | | | 0.4 | 1 |
| CCT | | | | | | | 0.60 | | | | 0.4 | 1 |
| ICG | | | 0.1 | | | | | 0.5 | | 0.3 | 0.1 | 1 |
| OCT | | | | | | | 0.4 | | | | 0.6 | 1 |
| OGT | | | 0.2 | | | | | 0.5 | | 0.1 | 0.2 | 1 |
| GCT | | | 1 | | | | | | | | 0 | 1 |
| GGC | | | 0.6 | | | | | | | 0.1 | 0.3 | 1 |
| CHP | | | 0.6 | | | | | | | | 0.4 | 1 |
| SHY | | 1 | | | | | | | | | | 1 |
| WND | | | | | 1 | | | | | | | 1 |
| DPV | | | | | | 1 | | | | | | 1 |
| BGT | | | 0.1 | | | | | 0.5 | | 0.3 | 0.1 | 1 |
| RPV | | | | | | 1 | | | | | | 1 |
| BF2 | | | | | | | | 0.7 | | | 0.3 | 1 |
| FCV | | | | 1 | | | | | | | | 1 |
| SFC | | | | 1 | | | | | | | | 1 |
| MFC | | | | 1 | | | | | | | | 1 |

# 3. IMPLEMENTATION OF 2FLC'S IN MARKAL

## 3.1 Introduction

As explained in Section 2.1, ECN did not implement 2FLC's in MARKAL directly, but developed and used an indirect approach. The explanations in this Chapter are solely meant for the MARKAL community, as they are rather specific for MARKAL.

In this chapter, the focus is therefore on the changes to the MARKAL model (i.e. source code level and controlling level) in order to accommodate the following SAPIENT-specific requirements:

- the use of the 'cluster of technologies' concept in conjunction with the Windows-based MARKAL user-interface (ANSWER),
- the ability to perform multiple MARKAL runs easily: this has been used to perform the MARKAL R&D shocks (see Chapter 5) and the MARKAL Monte Carlo runs (see Chapter 4),
- changes to the MARKAL ETL output module in order to provide the relevant information for the ISPA objectives (ISPA stands for Integrating System for Priority Assessment, and is the central model developed within the SAPIENT project, see (SAPIENT, 2003).

These requirements are discussed below in Sections 3.2 to 3.4. These changes have been implemented in the MARKAL model source code version of 2000.

## 3.2 Clusters of technologies

A 'cluster of technologies' is defined as a group of technologies sharing a common essential component. This component, which can be a technology in itself, is called the 'key technology' and is selected as the learning component in each of the technologies in the cluster. Examples of key technologies and, correspondingly, clusters of technologies are gas turbines, fuel cells, photo-voltaic (PV) modules, wind turbines, steam turbines, and boilers. The existing technologies need to be grouped into clusters of technologies which are similar with respect to their learning behaviour i.e. the development of these technologies is in some way linked to each other. One technology can appear in more than one cluster, e.g. an integrated coal gasification power plant is composed of, among other things, a gas turbine, a steam turbine, a gasifier and a boiler (Seebregts et al., 2000).

During the TEEM project, this concept was implemented rather 'ad hoc' and relatively cumbersome. For each cluster, the analyst had to add a user-defined constraint (or in MARKAL terminology: an ADRATIO). To be more flexible and to incorporate it in the most recent, Windows based user-interface, the MARKAL model was extended with the following equation (see Box 3.1 MARKAL for GAMS source code):

$\forall$ key $\forall$ tp $\geq$start key: INV(key, tp) = $\Sigma$ (tch in cluster of key) INV(tch, tp) $\times$ coupling factor(key, tch)

Thus in words: For all key technologies, and for all time periods (tp) including and exceeding the start year of the key technologies, the investment in the key technologies is the weighted sum of all technologies within the corresponding cluster. The weight is the so-called coupling factor of the key technology with the underlying technology.

The corresponding data that need to be entered/added, either in ANSWER or separate as '@INCLUDE' in the MARKAL GAMS data file, is the assignment of the coupling factors via the table CLUSTER(TEG, TCH), where TEG is the set of key learning technologies (with associated learning parameters). Set TEG defines the set of key technologies and is the label of the corresponding clusters. Set TCH defines the set of all technologies in the MARKAL model (TEG is a subset of TCH).

By default, CLUSTER(TEG, TCH) = 0. If CLUSTER(TEG, TCH) = cf ≠ 0 for a certain combination of two technologies A ∈ set TEG, and B ∈ TCH, say CLUSTER(A,B) = cf, then cf is the corresponding coupling factor.

For SAPIENT, ECN has made 10 clusters of technologies comprising 60 technologies (mainly supply side but also a few demand side technologies i.e. fuel cell vehicles). More details are given in Section 5.2.2. 'Clusters of technologies'.

Box 3.1 *GAMS source code equation that couples investments on (learning) key technology level to investments of technologies in the corresponding cluster*

```
*mmequac.ml to be included at end of mmequa.inc/ms/reg
*    %1 - equation name prefix 'EQ' or 'MS' or 'MR'
*    %2 - SOW indicator => '' or 'SOW,' or ''
*    %3 - coef qualifier => '' or '' or '_R'
*    %4 - variable/coef prefix => '' or 'S_' or 'R_'
*    %5 - REGional indicator => '' or '' or 'REG,'
*    %6 - regional scaling => '' or '' or '(REG)'
*    %7 - loop control set => 'TPTCH(TP,TEG)' or 'TPNTCH(TP,SOW,TEG)' or
'TPTCH_R(REG,TP,TEG)'
*
*AS, 28/01/00 coupling equation for key in TEG to cluster TCH's
*only if TCH in cluster TEG and TEG NE TCH
%1_CLU(%7)$((ORD(TP) GE
TCH_STRT%3(%5TEG))*NTCHTEG%3(%5TEG))..%4INV(%5TP, %2TEG) =E=
  SUM(TCH%3$(CLUSTER%3(%5TEG,TCH%3)*(ORD(TP) GE TCH_STRT%3(%5TCH))),
    CLUSTER%3(%5TEG,TCH) * %4INV(%5TP,%2TCH)
   );
```

## 3.3 Multiple runs feature

Specifically meant for SAPIENT purposes, ECN modified the controlling MARKAL BATch file 'ANS_RUN.BAT'. This file was changed in two ways:

1. to enable a consecutive execution of either the Reference run plus the 10 corresponding R&D shock runs, or the Soft Landing run plus the 10 corresponding R&D shock runs,
2. to enable the Monte Carlo experiments with MARKAL (See Chapter 4), with the number of runs set to 100, and with appropriate pre- and post-processing.

## 3.4 Modification to MARKAL ETL output module

The MARKAL ETL output module has been modified in two ways:

1. to accommodate the new way of modelling clusters of technologies,
2. to provide specific output needed for computation of some of the ISPA objectives.

Table 3.1 presents a total overview of the MARKAL files affected and modified.

Table 3.1 *Changed MARKAL controlling and source code files*

| File type | Specific Files modified |
|---|---|
| Controlling BAT files | ANS_GAMS.BAT<br>(Changed version number and indicated files affected compared to previous version)<br>ANS_RUN.BAT<br>(changed in order to perform multiple runs, can be tailor made for specific R&D shock runs, or Monte Carlo runs) |
| Standard MARKAL source code | MMINCLUD.INC, MMINIT.INC, MMEQUA.INC, MODEL.MRK |
| Specific ETL MARKAL source code | Coefficients and equations files:<br>MMCOEF.ML<br>MMEQUAC.ML<br>ETL Output module files:<br>ATLEARN.ML<br>ATLEARN1.ML<br>ATSC.ML (includes specific ISPA objectives output: sales and investments learning technologies, $CO_2$ emissions and energy system costs)<br>ATLEARN8.ML<br>ATLEARN9.ML |

# 4. MARKAL MONTE CARLO EXPERIMENTS

## 4.1 Introduction

This section describes the experimental use of Monte Carlo analysis methods with the MARKAL model. These experiments were conducted in the beginning of 2001 with the MARKAL model source code version of 2000. Monte Carlo analysis is a method to analyse and propagate data uncertainties in models. Figure 4.1 shows the principle of Monte Carlo analysis (MCA).

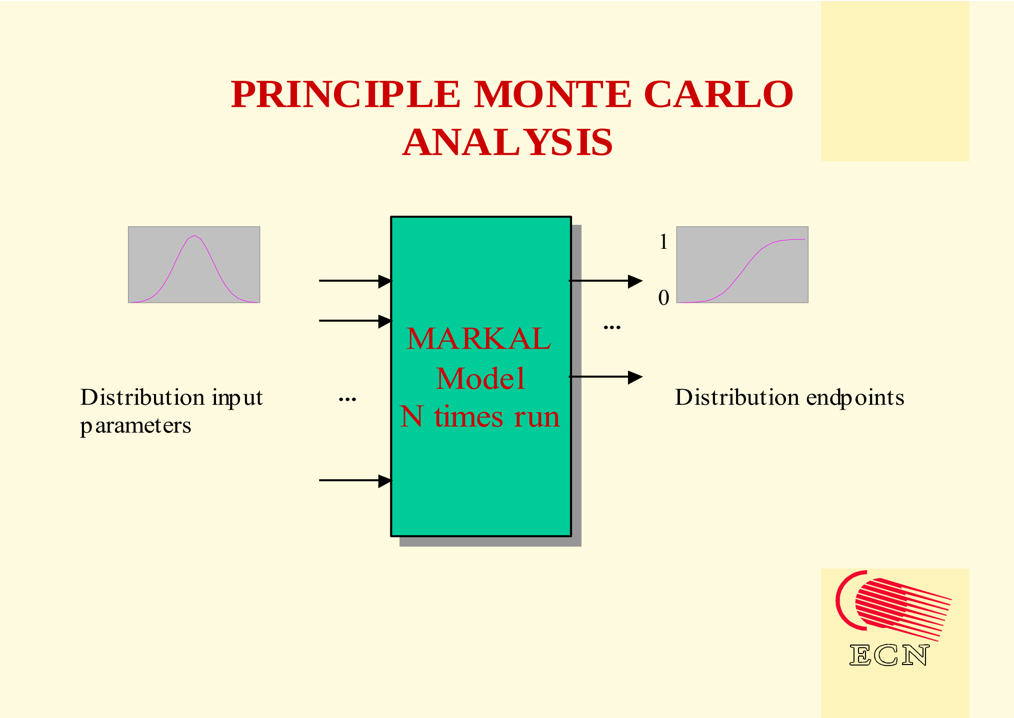



Figure 4.1 *Principle of Monte Carlo Analysis with MARKAL*

MCA is a relatively time-consuming (i.e. computationally) method. However, with the current speed and memory capabilities of PC's, Monte Carlo analysis with complex MARKAL models e.g. ECN's MARKAL model for Western Europe now becomes feasible. Monte Carlo analysis can be used complementary to conventional MARKAL practices as (in decreasing order of frequency of use):

- Scenario analysis
- Sensitivity analysis
- Stochastic programming and
- Cost-benefit analysis.

These approaches are described in e.g. (ETSAP, 1999; Ybema et al., 1995, 1998).

The MARKAL Monte Carlo experiments have been carried out as a kind of shadow calculation of the PROMETHEUS calculation. PROMETHEUS has been developed and used in the SAPIENT project (SAPIENT, 2003). The marginal cost of $CO_2$ reduction, as computed by PROMETHEUS for e.g. the EU, is the basic parameter for comparison. Like PROMETHEUS, the MARKAL Monte Carlo experiments result in a probability distribution for this parameter.

## 4.2 Monte Carlo methods compared to other approaches

To our knowledge, Monte Carlo (MC) uncertainty analysis methods have hardly ever - or even never - been applied to complex energy system models like MARKAL (see also Kann & Weyant, 2000). The main reason is probably that Monte Carlo analysis methods generally require a lot of model runs in order to obtain stable and sensible results. With the current speed of PC's and even with rather complex models like the EU MARKAL model, MC analysis is now feasible in terms of computational complexity and solution times. E.g. the ECN MARKAL long-term scenario study (Ybema et al., 1998) comprised about 60 models runs (2 scenarios with about 30 variants and sensitivity analyses for each scenario). From other type of MC analysis applications, it is known that even 100 runs can be sufficient to produce meaningful results if a stratified sampling method such as Latin Hypercube Sampling is applied (IAEA, 1989). From the first experiments conducted by ECN and reported here, it appears that MC analysis can be used in combination with scenario analysis, even with ECN's Western European MARKAL model (e.g. see (Lako et al., 1998)) and including technology learning (e.g. see Seebregts et al., 2000).

## 4.3 What type of uncertainties can be addressed?

Monte Carlo analysis can give an indication of the parameter and data uncertainties within one particular scenario. The main results derived from a MC analysis are:

- A probability distribution (and hence, indicators like means, variance, spread, percentile points) of the results of interest ('endpoints').
- A ranking of the uncertain parameters based on their contribution to the uncertainty in selected endpoints.

The spread obtained this way can also show whether different scenarios can overlap in some instances. Model structure, more methodological (e.g. using ETL or not/using 1FLC or 2FLC) uncertainties and 'incompleteness' uncertainties cannot be dealt with this type of analysis. Sensitivity analyses or analyses with different model variants are better suited to address such uncertainties.

In first instance, the parameters to be addressed in such an MC analysis should be restricted to parameters not typically characterising the scenario. So, typically uncertainties associated with technology characteristics are candidate to be included in a Monte Carlo analysis: Investment costs; O&M costs; efficiencies, maximum growth rates (e.g. due to production limits), physical potentials (e.g. onshore wind turbines), progress ratios, etc. However, parameters characterising the scenario parameters can also be included[3].

## 4.4 Example: Uncertainties in progress ratios solar PV and wind turbines

The Monte Carlo (MC) experiments have been performed with the Soft Landing $CO_2$ reduction limits (Blanchard et al., 2000), see also Section 5.3 'Scenario assumptions'. The focus has been on the uncertainties in progress ratios, in particular for solar PV and wind turbines. This section summarises the inputs and main results, including a comparison with PROMETHEUS results. Next, the development of investment cost and installed capacity is given as more conventional indicators of the market penetration of the two learning technologies. Finally, a comparison is made with 4 (traditional) deterministic analyses.

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[3] economic and demographic (energy demands, energy prices), market and production related (market penetration constraints, growth rates), 'environmental' (resources, emission constraints, physical potential), discount rate (coupled to investment decisions) or the social rate of time preference.

### 4.4.1 Ranges for progress ratios

Uncertainties in progress ratios, among others, are one of the key uncertainties associated with modelling of technological learning in energy models. E.g. from (Kram et al., 2000; McDonald & Schrattenholzer, 2001; and Junginger, 2000) the following ranges can be deduced for the progress ratio on specific (investment) cost.

Table 4.1 *Uncertainty ranges progress ratios solar PV modules and wind turbines (learning curve for inv. cost/kW(p))*

| Technology | Kram et al., 2000 | McDonald & Schrattenholzer, 2001 | Junginger, 2000 |
|---|---|---|---|
| Solar PV (modules) | 0.72-0.85 | 0.80 | - |
| Wind energy, wind turbines | 0.85-0.90 | 0.83-0.92 | 0.85-0.96 |

Based on the various reported progress ratios in (Kram et al., 2000 and Junginger, 2000), the following probability distributions have been chosen. The ranges are based on (Junginger, 2000) for wind turbines, and on the range arising from the values used in the models MESSAGE, POLES, ERIS, and MARKAL (Kram et al., 2000)). The mean values are the values as derived by ECN (Seebregts et al., 1998).

Table 4.2 *Probability distributions progress ratios Solar PV and Wind turbines*

| Technology | Distribution | Mean value | Remarks |
|---|---|---|---|
| Solar PV (modules) | Uniform (0.76 ; 0.88) | 0.82 | - |
| Wind energy, wind turbines | Triangular (0.85 ; 0.90 ; 0.96) | 0.90 | 0.85 and 0.96 are about 5-th and 95-th percentile point |

### 4.4.2 Marginal cost $CO_2$ reduction and comparison with PROMETHEUS

The resulting marginal cost of reducing $CO_2$ as computed from the MARKAL results is given in the next table. As can be seen, the mean values for 2010 and 2030 (128 and 63 euro) are much higher than the corresponding values from PROMETHEUS. For 2010 also the minimum and maximum differ a lot (2030 PROMETHEUS values other than the mean are not known).

Table 4.3 *Marginal Cost of $CO_2$ reduction [€/t$CO_2$]. Between brackets, the corresponding PROMETHEUS values [$95]*

| | 2010 | 2030 | 2040 | 2050 |
|---|---|---|---|---|
| Maximum | 145 [54 $95] | 67 | 76 | 99 |
| 95-th perc. Point | 141 | 67 | 75 | 98 |
| Mean | 128 [15 $95] | 63 [33 $95] | 66 | 94 |
| 5-th perc. Point | 122 | 53 | 59 | 91 |
| Minimum | 122 [0 $95] | 52 | 56 | 91 |

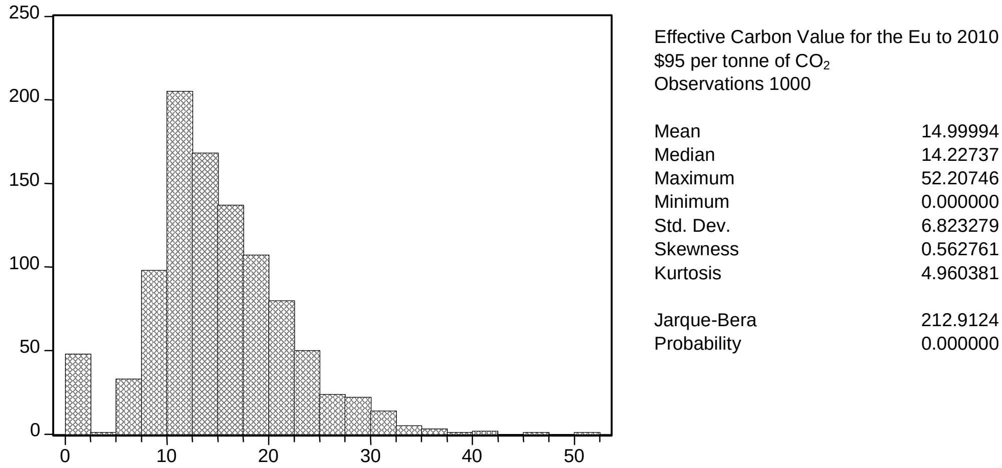


Figure 4.2 *Distribution carbon value 2010 EU (from PROMETHEUS model runs)*

### 4.4.3 Development of investment cost and capacity

The next tables show the results for the endpoints 'Investment cost' and 'Capacity' in de model years 2030 and 2050. As can be seen with respect to the progress ratios, the means and other distribution indicators are in line with the input distributions defined. The ranges in investment cost and capacity are rather large. It is important to note that the values now depicted as e.g. 5-th percentile point are not belonging to the same model run. A rather low cost of solar PV does not match with low values for capacity. In fact, the corresponding values for investment cost should be 'mirrored', i.e. a minimum for cost corresponds with the maximum for capacity. So e.g. 344 €/kWp in 2030 for solar PV matches with 172 GWp capacity in 2030.

The results show that the success of the two technologies is very dependent on the value of the progress ratio. In a few cases, solar PV does not enter the market, except on a level caused by a lower bound in the model. In a few other cases, solar PV goes to its maximum [300 GWp].

Table 4.4 *Investment cost and capacity installed, 2030 and 2050, from 100 MC runs*

| Results solar PV | pr_PV (input) | i.c.2030 [€/kWp] | i.c.2050 [€/kWp] | cap. 2030 [GWp] | cap. 2050 [GWp] |
|---|---|---|---|---|---|
| Minimum | 0.761 | 344 | 260 | 1 | 1 |
| 5-th perc. Point | 0.765 | 373 | 282 | 1 | 1 |
| Mean (input) | (0.820) | | | | |
| Mean | 0.819 | 1833 | 1565 | 55 | 176 |
| 95-th perc. Point | 0.872 | 3619 | 3441 | 165 | 300 |
| Maximum | 0.880 | 3767 | 3611 | 172 | 300 |
| Maximum (input value) | | | | (300) | (300) |
| **Results Wind turbines** | **pr_wind (input)** | **i.c.2030 [€/kW]** | **i.c. 2050 [€/kW]** | **cap. 2030 [GWp]** | **cap. 2050 [GWp]** |
| Minimum | 0.863 | 322 | 271 | 42 | 77 |
| 5-th perc. Point | 0.870 | 360 | 309 | 58 | 102 |
| Mean (input) | (0.900) | | | | |
| Mean | 0.904 | 559 | 500 | 82 | 155 |
| 95-th perc. Point | 0.938 | 765 | 718 | 129 | 245 |
| Maximum | 0.954 | 934 | 876 | 134 | 245 |

### 4.4.4 Comparison with 4 deterministic cases

The next figures show the results in the SL scenario with the mean values of the two progress ratios. In addition, a Base scenario plus two R&D impact variants are shown. The Base scenario is the variant without $CO_2$ emission constraints. The R&D cases are cases with better progress ratios for solar PV (from 0.82 to 0.765, so to the lower limit of the MCA results distribution) and wind (from 0.90 to 0.897, so hardly any change). The changes in PR were made by application of the indirect approach see Section 2.2. In this deterministic case, the maximum of 300 GWp is not reached for solar PV, see Figure 4.4. From Figure 4.4. It also can be seen that the cumulative capacity bound has already been reached in 2040 in the SL R&D case. For wind energy, see Figure 4.5, the capacity in 2050 is about 150 GW in the SL R&D case, more or less equal to the mean of the MCA results (compare with table above).

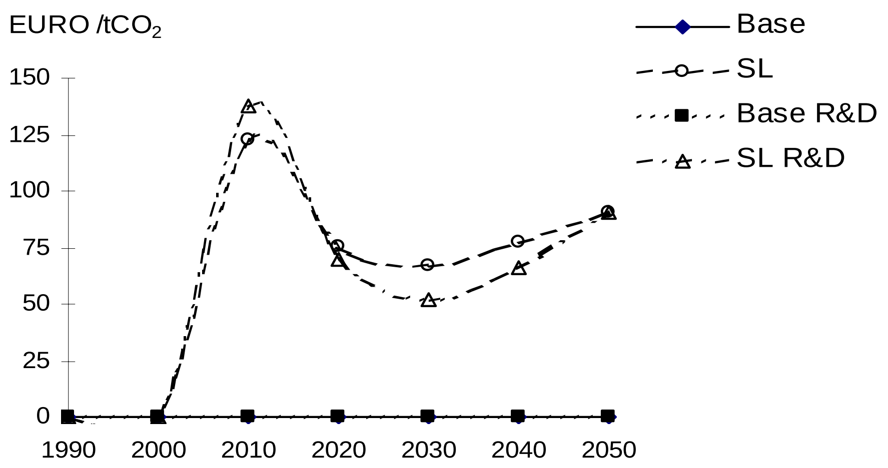


Figure 4.3 *Marginal cost of $CO_2$ reduction (Base = without $CO_2$ emission constraints; R&D = with better progress ratios)*

As can be seen, overall $CO_2$ costs are lower in the SL R&D case. Since Base is unconstrained, $CO_2$ cost equals zero.

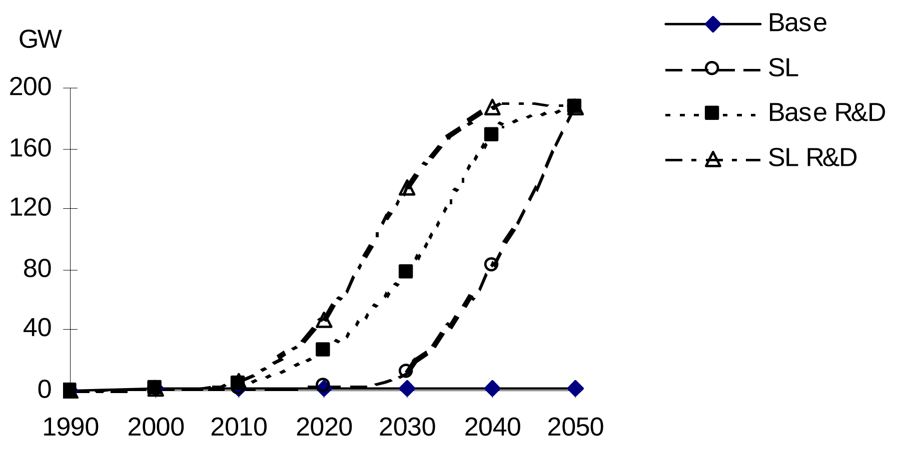


Figure 4.4 *Installed capacity solar PV (Base = without $CO_2$ emission constraints; R&D = with better progress ratios)*

As can be seen, R&D leads to elevated levels both in constrained (SL) and unconstrained (Base) case (up to a user-defined upper capacity bound). The three capacity curves show an S-type penetration curve, caused by using a maximal annual growth rate that is effective in the first periods. In the Base case without additional R&D, solar PV does not become attractive.

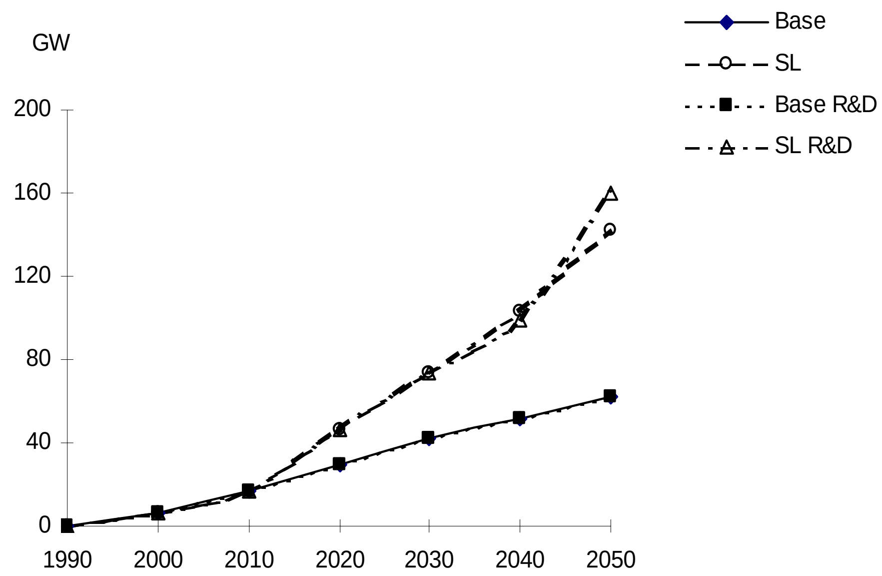


Figure 4.5 *Installed capacity Wind energy (Base = without $CO_2$ emission constraints; R&D = with better progress ratios)*

As can be seen, only in the constrained (SL) case, R&D leads to somewhat elevated levels for wind energy. Extra R&D has no or hardly any impact. Note that in the R&D case, solar PV seems to win over wind turbines from 2020 on.

It should be noted that the MC analyses and the SL/Base and R&D analyses outlined above, have been performed prior to the final MARKAL R&D shock runs, as reported in Chapter 5 . The main differences are the number of clusters (here: only 2; R&D shocks Chapter 5) and different bounds on the renewable technologies.

## 4.5 Monte Carlo analysis as pre-processor of potentials and floor-costs

MC analysis can also be used as a step prior to executing MARKAL calculations. It is for example possible to test and check inputs of models, e.g. for technology learning parameters, it is possible to investigate the maximum potentials of learning technologies, as function of uncertain inputs. This potential can be expressed as: floor cost (i.e. the lowest investment cost that can be achieved when a technology is fully employed up to its upper limits), maximum number of doublings or maximum capacity that can be reached within the model time horizon. Inputs needed for this are: progress ratio, initial cost, initial cumulative capacity and maximum cumulative capacity. Uncertain parameters in this example are:
Pr = progress ratio
C0 = initial cumulative capacity (at start time horizon)
Cm = maximum cumulative capacity (at end time horizon)

Here an example is presented for the floor cost of solar PV modules. The distributions of the uncertain parameters are given in Table 3.5.

Table 4.5 *Example input distributions (EU MARKAL 1990-2050)*

| Parameter | Unit | Distribution |
|---|---|---|
| Progress ratio solar PV | - | Triangular (0,76; 0,82; 0,88) |
| Initial cumulative capacity solar PV | GWp | Uniform (0,05; 0,15) |
| Maximum cumulative capacity | GWp | Uniform (400; 800) |

An example of output displayed as Tornado diagram, is given below in Figure 4.6. This figure shows a Tornado diagram for the endpoint ‘floor cost’. As can be seen, the uncertainty in the progress ratio mostly determines the uncertainty in the floor cost. The higher the progress ratio (pr), the higher the floor cost (i.e. less learning potential). The higher the maximum cumulative capacity, the lower the floor cost (hence, more learning). The higher the initial cumulative capacity (C0), the higher the floor cost (i.e. less learning potential). Figure 4.7 shows the cumulative distribution function of the floor-cost of solar PV. A mean value of 560€/kWp is computed for 2050.

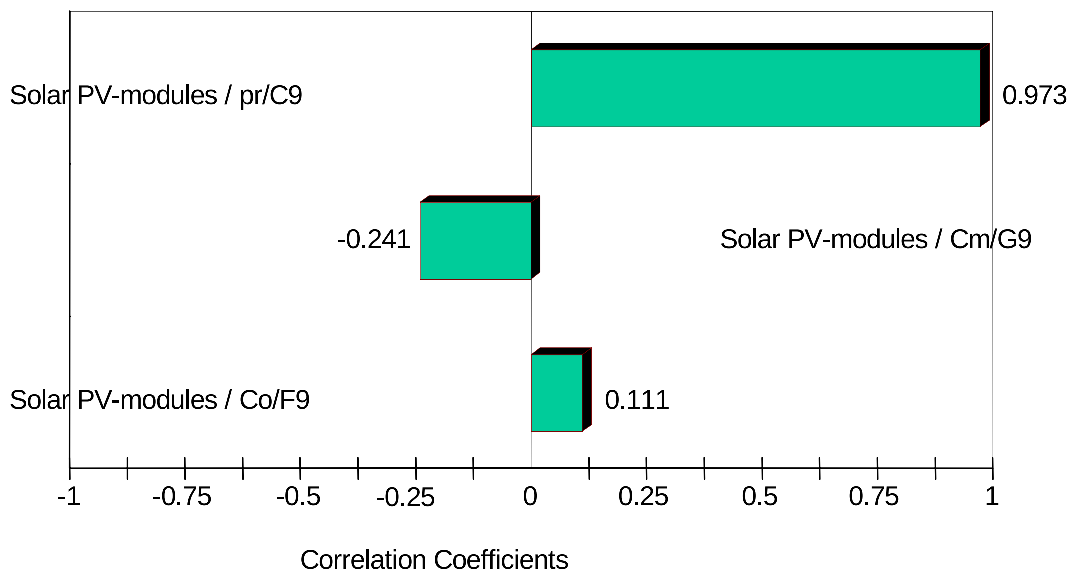


Figure 4.6 Example of Tornado diagram: more important uncertain input parameters are listed on top (figure directly copied from @Risk C9, G9, and F9 refer to Excel cells)

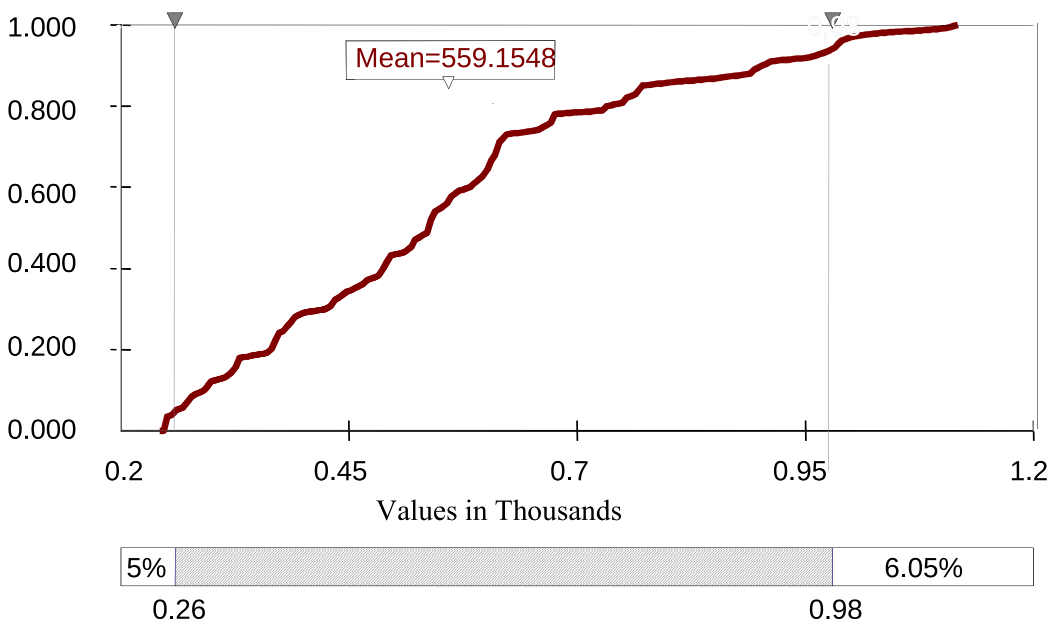


Figure 4.7 *Distribution of floor cost (figure directly copied from @Risk) in 2050*

Possibly, the life of a technology, bounds like maximum annual growth rates, capacity upper bounds or investment upper bounds can be added to further determine the maximum potential or the uncertainty. These latter parameters may result in a better estimate of first maximum cumulative capacity [Cm] as input to the actual MARKAL run with endogenous learning. However, this has not been done in the SAPIENT project.

Table 4.6 *Progress ratios selected for the MARKAL clusters of learning technologies*

| Code | | Description | Progress Ratio | Max. annual growth factor | Source of information or rationale |
|---|---|---|---|---|---|
| 1. | ESK | Solar PV modules | 0.82 | 1.35 from 1990-2000 1.25 thereafter | Updated from 0.81 from (Seebregts et al., 1998,) Section 3.4.1 to 0.82. (de Lange & Crommentuijn, 2000) show that 1.25 annual growth over longer periods (2000-2050) is rather optimistic |
| 2. | EWK | Wind turbine | 0.90 | 1.46 from 1990-2001 1.25 thereafter | PR Value has been underpinned in (Seebregts et al., 1998) Section 3.4.2 (de Lange & Crommentuijn, 2000) show that 1.25 annual growth over longer periods (2000-2050) is rather optimistic |
| 3. | FCK | Fuel cell | 0.82 | - | Value has been underpinned in (Seebregts et al., 1998) Section 3.4.3 |
| 4. | GFK | Gasifier | 0.9 | - | Generic value used in (Seebregts et al., 1999) which was based on (Neij, 1997) with gasifier termed as 'advanced' technology |
| 5. | GTK | Gas turbine | 0.87 | - | No recent statistics or references available, decided to use 'old' IIASA value (up to 1980) as estimate (McDonald & Schrattenholzer, 2001) |
| 6. | HYK | Hydro turbine | 0.997 | - | 1FLC fitted by ECN from base data derived from data supplied with (Criqui, 2001) |
| 7. | STK | Steam turbine | 0.99 | - | 0.99, as generic value for a more conventional technology that hardly learns |
| 8. | BOK | Boiler | 0.99 | - | 0.99, as generic value for a more conventional technology that hardly learns |
| 9. | CCK | Combined cycle boiler | 0.95 | - | 0.95, more advanced than a conventional boiler, and therefore a better progress ratio |
| 10. | NUK | Nuclear reactor | 0.99 | - | 0.99, as generic value for a more conventional technology that hardly learns |

## 4.6 Use of @Risk as pre and post-processor of MARKAL runs

The @RISK software (Winston, 1999) has been used as pre-processor and post-processor of the MARKAL runs; @RISK is an Excel add-on. The series of input samples are made using @Risk. Output of @Risk has been converted to appropriate text data ('DD' files in MARKAL terminology) files to be used in the ANS_RUN.BAT file. The uncertainty measures, i.e. correlation coefficients between inputs and results are computed afterwards. The next box provides some more details of the sequential steps.

Box 4.1 *MARKAL-1. Detailed steps*

1. Establish uncertain input parameters and their distributions (in the first test with a MARKAL learning model: only progress ratios for Solar PV and Wind turbines, just to illustrate the approach) -> IN @Risk.
2. Generate input sample (for each of the M scenarios/variants) -> IN @Risk and Excel: inputs are also selected as output in order to obtain samples from @Risk.
   Colums in @Risk Data Window are copied to a separate XLS file. This last XLS file is edited somewhat, written to a text file.
3. Convert these samples to MARKAL input files in the appropriate format
   With BAT and Pascal utility program: Text file from step 2 is processed to appropriate format. For each sample a separate file is made.
4. Run MARKAL M x N (N=100) times.
5. Derive the endpoints from these results. $CO_2$ emissions, capacities of (selected) technologies.
6. Derive spread, distribution of these endpoints/indicators and correlations with the uncertain input parameters, or correlations between outputs.

Step 1-3 is a kind of pre-processing (outside MARKAL)
Step 4-5 is integrated into MARKAL source and batch files (only 1 GAMS source file that to filter the relevant and desired endpoints (results) in each run and 1 DOS BAT file (ANS_RUN.BAT) file.

All other MARKAL/ANSWER source files can be left unchanged.
Step 6 is a post-processing (outside MARKAL and preferable in @Risk since it contains a number of useful features).

## 4.7 Conclusions experiments

Despite the limitations in the MC analyses (e.g. only 2 clusters of learning technologies, only progress ratios as uncertain parameter), we conclude from these experiments:

- Monte Carlo analysis can be applied for complex MARKAL models.
- Further research is needed to conclude definitely that it is a feature to be included as 'member' of the official family of MARKAL models (Seebregts et al., 2001).
- The uncertainty in the input data for learning can be analysed well with a combination of sensitivity analyses and Monte Carlo analyses.
- The uncertainty range in the wind turbine progress ratio (PR), as derived from literature (0.83-0.96, see Table 4.1), is much larger than the impact of R&D on the progress ratio (see also Table 5.9 in next chapter). Therefore, given the impact from the R&D assumption on the wind turbine PR, for wind turbines no robust conclusions can be derived solely on R&D impacts. The uncertainty in the PR, which can be caused by a variety of factors, seems far more important. This finding supports the idea that it is more important to obtain good data for the one-factor learning curve parameters, than to introduce a more complex two-factor learning curve (either indirect or direct).

# 5. IMPACT OF R&D (‘SHOCKS’) ON POLICY OBJECTIVES USING MARKAL

## 5.1 Introduction

This chapter describes the results of the EU MARKAL runs for the SAPIENT project (MARKAL SAPIENT 2001 database). It is structured as follows. In Section 5.2 assumptions on technologies data, including the concept of clusters of technologies and bounds applied will be presented. Section 5.3 discusses assumptions on scenarios and R&D ‘shocks’ that are applied in variants. Section 5.4 briefly discusses the type of results. The results themselves are presented in Section 5.5. The chapter ends with some conclusions and recommendations.

## 5.2 Technologies: data and other assumptions

### 5.2.1 MARKAL SAPIENT 2001 database

In the TEEM (Energy Technology Dynamics and Advanced Energy System Modelling) project, the predecessor of SAPIENT, the European MARKAL database was used (Seebregts et al., 2000). For the SAPIENT project, this database has been extended with biomass technologies based on the more detailed MATTER data (Gielen et al., 2000). The most important changes (i.e. on bounds) are discussed in Section 5.2.4.

### 5.2.2 Clusters of technologies

*Approach*

The approach followed by ECN Policy Studies on the modeling of technological progress in the MARKAL Europe model uses the concept of ‘clusters of technologies’ (Seebregts et al., 2001). In total, 10 clusters of learning technologies are implemented, representing in total 60 technologies. A ‘cluster of technologies’ is defined as a group of technologies sharing a common essential component.

This component, which can be a technology in itself, is called the ‘key technology’ and is selected as the learning component in each of the technologies in the cluster. Examples of key technologies and, correspondingly, clusters of technologies are gas turbines, fuel cells, photovoltaic (PV) modules, wind turbines, burners and boilers.

The existing technologies need to be grouped into clusters of technologies which are similar with respect to their learning behavior i.e. the development of these technologies is in some way linked to each other. One technology can appear in more than one cluster. For example, an integrated coal gasification power plant is composed of, among other things, a gas turbine, a steam turbine, a gasifier and a boiler (Seebregts et al., 2000).

To implement the concept of clusters in MARKAL, the following approach has been followed:

- Identify the clusters and key technologies from the technology database.
- Review the characteristics of the technologies in each cluster.
- Add the common component as key technology to the technology database.
- Make the key technology a learning technology and assign the learning parameters to it.
- Assign a coupling factor to the key technology and the technologies in the corresponding cluster.

- Calibrate all learning parameters so that they are in line with the currently available cost and capacity data.
- Adjust the characteristics of the remaining parts of the technologies in the corresponding cluster.

When considered necessary, adjust the bounds (or other parameters) of the key technologies or the technologies in the clusters. All steps described above have been gone through during the TEEM project in which the concept of clusters of technologies has been tested (Seebregts et al., 1999; Seebregts et al., 2000). During the SAPIENT project the model has been improved. Besides the extension of the number of technologies in the database (as mentioned above), also the number of clusters has been doubled (from five to ten). Therefore, we will now concentrate on step 1 of the approach: identification of clusters and key technologies in SAPIENT.

### *Identification of clusters*

The approach described above was applied for the clusters (last five are new compared to TEEM): wind turbines (WT), solar PV modules (PV), fuel cells (FC), gasifiers (GF), gas turbines (GT), hydro turbines (HY), steam turbines (ST), boiler (BO), combined cycle boiler (CC) and Nuclear Reactor (NU). These ten clusters together represent in total about 60 individual MARKAL technologies. For SAPIENT, these clusters and technologies have also been mapped to the POLES technologies. The mapping from our clusters to the 24 POLES technologies is not a 1-to-1 relationship. The technologies (incl. their codes) considered in MARKAL and POLES are summarized in Annex A.

Table 5.1 summarizes the clusters and key technologies used in MARKAL. In total 59 technologies are involved. Because of the fact that some of the technologies belong to more than one cluster, the numbers in Table 5.1 add up to 123.

Table 5.1 *Clusters of learning technologies*

| Code | Description | # technologies in cluster |
|---|---|---|
| ESK | Solar PV modules | 5 |
| EWK | Wind turbine | 4 |
| FCK | Fuel cell | 11 |
| GFK | Gasifier | 15 |
| GTK | Gas turbine | 23 |
| HYK | Hydro turbine | 5 |
| STK | Steam turbine | 29 |
| BOK | Boiler | 14 |
| CCK | Combined cycle boiler | 16 |
| NUK | Nuclear reactor | 1 |

Table 5.2 illustrates the cluster of gasifier technologies. As indicated in Table 5.1, for the key technology ‘gasifier’, the cluster consists of 15 technologies. The cumulative installed capacity for gasifiers is based on the combination of the capacities of these 15 individual technologies. Table 5.2 also clearly illustrates that technologies can belong to more than one cluster.

Table 5.2 *Clusters of gasifier technologies*

| Description | Key/cluster |
|---|---|
| Lignin gasifier large industrial cog. | GTK STK GFK |
| Wood gasification small industrial cog. | GTK STK GFK |
| Wood gasification CC power plant | GTK STK GFK CCK |
| Biomass gasifier dedicated CC (NH) | GTK STK GFK CCK |
| Biomass gasifier SOFC | GTK STK GFK FCK CCK |
| IGCC with co-gasification of biomass | GTK STK GFK CCK |
| Biomass gas turbine plant | GTK GFK |
| Biomass gasifier dedicated CC (NH) STW | GTK STK GFK CCK |
| Biomass gasifier FT-fuel/ele co-prod | GTK STK GFK CCK |
| Integrated coal gasification power plant | GTK STK GFK CCK |
| Integrated lignite fired power plant | GTK STK GFK CCK |
| Integrated Coal Gasification SOFC plant | GTK STK GFK FCK CCK |
| Existing CC power plant | GTK STK GFK CCK |
| Waste to energy plant (Lurgi gasifier) | STK GFK |
| Waste to energy plant (Gibros PEC) | STK GFK |

Each technology is composed of (or in other words can be coupled to) one or more key technologies. As explained earlier, a key technology is the learning component in each of the technologies in a cluster. However, besides the learning part of a technology (i.e. the part consisting of one or more key technologies), also a non-learning part exists.As an example to explain the use of so called 'coupling factors' in MARKAL, we take an integrated coal gasification (or IGCC) power plant. According to Table 2 this technology belongs to four clusters of key technologies, i.e. gas turbine, steam turbine, gasifier and combined cycle boiler. Coupling factors 'couple' the 10 key technologies to the 60 technologies that are actually learning in MARKAL. The actual value of the coupling factor is based on the output capacity of the technology concerned. For a combined cycle-gasifier combination (as in the example) it is assumed that 60% of the capacity is in the gas turbine and the other 40% is in the steam turbine. Correspondingly, the coupling factor for the gas turbine is 0.6 and for the steam turbine is 0.4.

The coupling factors are for instance used to calculate the (remaining) investment costs of the non-learning part for each technology. The investment of the learning part is determined by the combination of key technologies. For the IGCC the breakdown of investment costs is illustrated in Table 5.3.

Table 5.3 *Example of cost breakdown IGCC (in €$_{1995}$/kW installed capacity)*

| Technology | Cost | Coupling factor |
|---|---|---|
| New integrated coal gasification p.p. (as a whole) | 1510 | |
| Gas turbine (as key) | 380 | 0.6 |
| Steam turbine (as key) | 300 | 0.4 |
| Gasifier (as key) | 640 | 1.0 |
| CC boiler (as key) | 450 | 0.4 |

A complete new integrated coal gasification power plant in total costs 1510 €/kW installed. Of these costs, $0.6 \times 380 = 228$ €/kW is related to the costs of the gas turbine. Correspondingly, $0.4 \times 300 = 120$ €/kW is related to the costs of the steam turbine. The so-called 'non-learning part investment cost' is defined as the 'total investment costs of a new technology - weighted investment costs of the corresponding key technologies'. In this example, the non-learning part (referring to 2000) is then calculated as follows:

$$1510 - \{ 0.6 \times 380 + 0.4 \times 300 + 1.0 \times 640 + 0.4 \times 450 \} = 1510 - 1166 = 342$$

The weighted investment costs of the four key technologies sum up to 77% (i.e. 1166/1510) of the total investment costs of the new integrated coal gasification power plant. For 2010 and further, the 'non learning part investment cost' in the EU MARKAL database becomes (342/1510=) 0.23 × original value (i.e. the value used before the concept of clusters including the accom-panying cost breakdown was introduced; in the case of an IGCC this value is 1510). In Annex B, a summary is given of all the coupling factors that are used in the SAPIENT project.

### 5.2.3 Learning parameters

To the extent possible, learning parameters have been updated and harmonized with IEPE's database (Criqui, 2001). Both the alternative approach of two-factor learning curves in MARKAL and the estimation of the progress ratios for the MARKAL clusters of learning technologies have used IEPE's database as a source of information.

Other learning parameters (i.e. initial and maximum cumulative capacity, growth factors, constraints) have been selected largely based on the original MARKAL TEEM database. Table 5.4 gives an overview of most important learning parameters of key technologies implemented in the SAPIENT database. For clarification, a few definitions will be given below (Seebregts et al., 2000).

*Progress ratio*

The progress ratio expresses the rate at which the cost declines each time the cumulative capacity doubles. E.g. a progress ratio of 0.8 means that the costs per unit of newly installed capacity decrease by 20% each time the cumulative installed capacity is doubled. The progress ratio thus constitutes a key factor for technological progress because it determines the speed of learning for the technology.

*Initial costs*

The initial costs form part of the costs of each technology belonging to the cluster. The initial costs (for 1990) are calibrated based on the costs of the technology today (i.e. the cost 2000). The costs for the year 2000 are used to calculate the investment of the learning part of a technology, as was shown in Table 5.3.

*Initial cumulative capacity*

The initial cumulative capacity of all technologies in a cluster can be derived from the original database (i.e. without learning) by adding the residual capacities for the year 1990 and the capacity installed during the period 1990-1999 of the separate technologies. Current capacity figures (e.g. for wind energy in Western Europe nowadays (beginning of 2002) already 13 GW is installed) have been used to calibrate the initial capacity data.

*Maximum cumulative capacity*

The maximum cumulative installed capacity is defined for the year 2050. The common value of 1000 GW (except steam turbines, for which 1500 GW was taken) was taken arbitrarily, but turned out well. For each key technology, the cumulative capacity in a certain period is calculated by the weighted sum (based on the coupling factors) of the cumulative installed capacities of the technologies in the specific cluster.

*Implied floor costs*

The implied floor costs are the costs when the maximum cumulative capacity is reached in 2050, i.e. this is the minimum level of costs that can be reached for a certain technology. The percentage of cost reduction is a good measure for the innovative nature of the technology and hence of its learning potential. E.g. for solar PV modules a cost reduction of approx. 93% is maximally possible, based on the parameters and learning parameters used.

Table 5.4 *Learning parameters of key technologies*

| Cluster | Progress Ratio[-] | Initial cost1990 (calibrated) [€95/kW] | Cost 2000 [€95/kW] | Initial Cumulative Capacity 1990 or start year[GW] | MaximumCumu-lative Capacity 2050 [GW] | Implied 'floor'-costs 2050[€95/kW] | Floor-cost as % of initial cost[%] | Maximun Number of doublings[-] |
|---|---|---|---|---|---|---|---|---|
| Solar PV | 0.82 | 7500 | 4000 | 0.1 | 1000 | 537 | 7.2 | 13.3 |
| Wind turbine | 0.90 | 1400 | 800 | 0.147 | 1000 | 366 | 26.2 | 12.7 |
| Fuel cell | 0.82 | 2650 | 1325 | 0.08 | 1000 | 178 | 6.7 | 13.6 |
| Gasifier | 0.9 | 800 | 640 | 0.65 | 1000 | 262 | 32.8 | 10.6 |
| Gas turbine | 0.87 | 450 | 380 | 31.9 | 1000 | 225 | 50 | 5 |
| Hydro turbine | 0.997 | 300 | 300 | 23 | 1000 | 295 | 98.4 | 5.4 |
| Steam turbine | 0.99 | 300 | 300 | 250 | 1500 | 292 | 97.4 | 2.6 |
| Boiler | 0.99 | 510 | 510 | 122 | 1000 | 508 | 99.6 | 0.45 |
| CC boiler | 0.95 | 500 | 450 | 1.17 | 1000 | 331 | 66.2 | 8.1 |
| Nuclear | 0.99 | 1940 | 1940 | 118 | 1000 | 1881 | 97 | 3.1 |

### 5.2.4 Bounds

It would go too far to elaborate on all the bounds applied in the model. Therefore, only capacity bounds on the key technologies 'Solar PV modules' and 'Wind turbines' will be briefly discussed here. For a complete overview of individual technology bounds applied, see Annex C.

#### *Solar PV*

For Solar PV, a minimum capacity bound of 3 GW (2010) was introduced, corresponding to the EU White Paper (1997). This was modelled as follows:

Table 5.5 *Lower capacities bound on total Solar PV in GW (scenario NOREBNDS)*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATSOLARLO | Total Solar PV (= ∑ES1-ES5) | 0 | 0 | 3 | 3 | 3 | 3 | 3 |

#### *Wind*

The potentials for Wind (onshore and offshore) are based on the latest DG TREN scenarios (LREM modelling, 2002). This was modelled as follows:

Table 5.6 *Upper capacity bounds on Wind in GW (scenario NOREBNDS)*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATWTON | Total wind onshore (EW4+5) | 1 | 13 | 72 | 103 | 123 | 130 | 136 |
| RATWTOFF | Total wind offshore (EW6+7) | 0.09 | 0.5 | 6.5 | 57 | 103 | 135 | 148 |

For offshore Wind, also a minimum capacity bound of 5 GW (2010) was introduced, based on the prognoses of EWEA (EWEA, 2001). This was modelled as follows:

Table 5.7 *Lower capacities bound on offshore Wind in GW (scenario NOREBNDS)*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATWTOFFLO | Total wind offshore (EW6+7) | 0 | 0 | 5 | 5 | 5 | 5 | 5 |

## 5.3 Scenario assumptions

### *Base cases and variants*

The baseline scenario (or the Reference Run) to be used in the model runs is the so called 'Market Drive' scenario with high renewable (abbreviated 'MD-hr' and described in Seebregts et al., 2000) including $CO_2$ costs of 15 €/ton till 2010 and 33 €/ton till 2030 (as agreed upon in the project). ECN has not harmonized the MARKAL MD-hr scenario with the POLES reference scenario and IIASA A1B scenario, except for a technology mapping of MARKAL and POLES technologies, and comparison of progress ratios used.

At the request of the European Commission, the overall (social) discount rate used will be 4% throughout. The calculation period is 1990-2050 (7 time periods of 10 years). The results to be used as an input to the ISPA model, are reported till 2030. Other results will be reported till 2050.

Besides the baseline scenario or Reference Run, the following variants of the baseline will be calculated:

- R&D 'shocks' (see below)
- 'Constrained $CO_2$' case translated from the POLES 'Soft Landing Stabilization' scenario (described in Blanchard et al., 2000). This runs are done as a kind of expected carbon limitation scenario, since based on previous ECN experiences (Kram et al., 2001; Gielen et al., 2000; Lako et al., 1998) with the carbon values as agreed (i.e. 15 €/ton till 2010 and 33 €/ton till 2030) no significant $CO_2$ reduction is achieved. Table 5.8 shows the applied $CO_2$ constraints in this scenario (from now on referred to as 'Soft Landing').

Table 5.8 *$CO_2$ constraints in the Soft Landing scenario (as percentage of 1990 level)*

| | 1990 | 2010 | 2030 | 2050 |
|---|---|---|---|---|
| EU MARKAL target $CO_2$ based on Kyoto 1,2,3 | 100 | 92.0 | 84.6 | 77.9 |
| EU MARKAL target $CO_2$ in % 1990 based on POLES reductions Soft Landing Scenario | 100 | 90.2 | 82.2 | 78.4 |

- This leads to 4 cases and variants:
  1. Baseline (Reference Run RR)
  2. Baseline plus R&D 'shocks' (RR+Shocks 1-10)
  3. $CO_2$ constraints according to Soft Landing figures POLES (SL)
  4. Soft Landing plus R&D 'shocks' (SL + Shocks 1-10).

### *R&D assumptions ('shocks')*

An additional R&D injection ('shock') will be applied on every key technology separately, i.e. this leads to a total of 10 so-called 'shock' runs. The R&D shock will be modeled in the time period designated as 2000. The effect of the R&D shock is assumed to be permanent i.e. the progress ratio will remains at the lowered value as a result of the shock.

As stated, the shocks will be applied at cluster level and the magnitude of the shock [in M€] will be fixed so as to achieve a significant[4] effect on the learning rate of the key technology involved. This is done to get an effect of the applied R&D-shock in the runs that serve as an input for the ISPA-model. Note that in the ISPA-model, the effect will be calculated *per additional €* of R&D, and therefore the actual size of the applied shock doesn't matter. As was already elaborated in Chapter 2, the additional R&D will have impact on the progress ratio according to relationship following relation: $\Delta PR = \Delta R\&D\text{-intensity} \times -0.289$.

[4] By 'significant' we mean a progress ratio improvement of at least 0.03 (but preferably 0.05). Such changes often changed the outcome of the model, based on experience with past MARKAL runs with learning. So, we set 0.03 as a target to cause the model to generate other solutions. However, for some technologies such a change could not or hardly be generated (see Table 5.9).

Table 5.9 summarizes the resulting shocks as applied at cluster level, including the impact of the additional R&D on the progress ratio (since in the MARKAL model the R&D shock is actually modeled as an ‘improved’ progress ratio). The parameter in Table 5.9 *n* is defined as the ‘level of the additional R&D-shock’ divided by the ‘level of the intended cumulative R&D for the period 2001-2010’, and is a measure of the relative level of the shock. As can be seen from Table 5.9, even a twenty-fold increase of the cumulative R&D for solar PV does not seriously effects its PR. Furthermore, an additional R&D input of over one 100 billion € for fuel cells has no serious impact on it’s PR, and consequently *n* is very large. This is due to a very low level of intended cumulative R&D (i.e. projected cumulative R&D 2001-2010, calculated based on the projected cumulative sales in the same time period), and should therefore not be valued as ‘unrealistic’. The same holds for hydro turbines and common boilers.

Table 5.9 *New Progress Ratio (PR) after R&D shock (in M$98)*

| Cluster | PR | R&D Shock | n | New PR | ΔPR | ΔR&D Intensity |
|---|---|---|---|---|---|---|
| Solar PV modules | 0.82 | 355000 | 21.7 | 0.792 | 0.028 | 0.10 |
| Wind turbine | 0.90 | 22000 | 2.5 | 0.85 | 0.049 | 0.17 |
| Fuel cell | 0.82 | 100000 | 654 | 0.791 | 0.029 | 0.10 |
| Gasifier | 0.9 | 1000 | 1.4 | 0.85 | 0.050 | 0.17 |
| Gas turbine | 0.87 | 5000 | 1.5 | 0.82 | 0.048 | 0.17 |
| Hydro turbine | 0.997 | 2000 | 2023 | 0.94 | 0.055 | 0.14 |
| Steam turbine | 0.99 | 6400 | 5.6 | 0.901 | 0.089 | 0.31 |
| Boiler | 0.99 | 4150 | 14.7 | 0.894 | 0.096 | 0.33 |
| Combined cycle boiler | 0.95 | 3000 | 1.0 | 0.90 | 0.049 | 0.17 |
| Nuclear reactor | 0.99 | 17500 | 1.0 | 0.94 | 0.049 | 0.17 |

## 5.4 Type of results wanted: R&D Objectives measurement

The following R&D objectives that can be used as inputs for the ISPA model, are calculated from the MARKAL results. All results are calculated for the period is 1990-2030, but since the model is calibrated for 1990, changes are related to 2000-2030.

- The measure of market impact (‘profitability’). This is defined as:
  *Discounted {(R&D induced technology cost + reference technology cost) × change in equipment sales volume} / R&D expenditure shock*
- The measure of impact on the $CO_2$ limitation objective. This is defined as:
  *Change in cumulative emissions/R&D expenditure shock*
- The measure of cost reductions to the consumer. This is defined as:
  *{R&D induced total discounted cost to the consumer - reference total discounted cost to the consumer} / R&D expenditure shock*

A fourth objective - the measure of the impact of security of supply - cannot be calculated as such, since oil and gas prices are exogenous inputs of the MARKAL model. As an alternative, the cumulative use/extraction of resources/imports could have been used in MARKAL. However, this measure did not fit into the ISPA model.

It was decided not to include (in ISPA) the fifth objective earlier defined, i.e. the measure of the impact on employment, because of lack of data on employment in the manufacture and development of technologies. This objective cannot be computed by MARKAL.

The results will be discussed in Section 5.5.

## 5.5 Results

Two sets of runs will be discussed here (referred to as 'set 1' and 'set 2'):

- Reference Run plus shocks (1-10)
- Soft Landing plus shocks (1-10).

First the ISPA inputs will be treated followed by (a selection of) other results.

### 5.5.1 ISPA inputs

Tables 5.10 and 5.11 show the ISPA objective values (as defined in Section 1.4) for run sets 1 and 2. The objectives are calculated from the model results as follows (NPV = net present value). All results are calculated for the period is 1990-2030.

- Impact on market profitability (unit M€/M€):
  *$NPV_{1990}$ [(specific technology cost in the 'Shock Run' + specific technology cost in the Reference Run)× 10 ×(investments in units of technology in the 'Shock Run' - investments in technology in the Reference Run)]} / R&D expenditure shock*
- Impact on $CO_2$ limitation objective (unit Mton $CO_2$/M€):
  *(10 x cumulative $CO_2$ emissions in the 'Shock' Run' - 10 x cumulative $CO_2$ emissions in the Reference Run) / R&D expenditure shock*
- Impact on cost reductions to the consumer (unit M€/M€):
  *$NPV_{1990}$ (10 ×energy system costs of the 'Shock Run' - 10 ×energy system costs of the Reference Run) / R&D expenditure shock*

The value of the energy system costs is used as a proxy for the costs to consumer.
The factor 10 appears from the fact that individual values reported represent the average of a 10 years' period, e.g. the value reported for the year '2000' is actually the average of the period 1995-2005.

Table 5.10 *Objectives measurement Reference Run + Shocks (1-10)*

| Case i.e. 'shock' on technology | NewPR (in case) | R&D shock M€ | Impact [1] onmarket ('profitability')M€/M€ | Impact on $CO_2$ [1] limitation objective Mton $CO_2$/M€ | Impact on cost [1] reductions to the consumer M€/M€ |
|---|---|---|---|---|---|
| Solar PV modules | 0.792 | 355000 | 0.0 | 0.0 | 0.0 |
| Wind turbine | 0.85 | 22000 | 0.0 | 0.0 | 0.0 |
| Fuel cell | 0.791 | 100000 | 0.0 | 0.0 | 0.0 |
| Gasifier | 0.85 | 1000 [2] | 6.1 | -0.8 [2] | -0.3 [2] |
| Gas turbine | 0.82 | 5000 | 0.0 | 0.0 | 0.0 |
| Hydro turbine | 0.94 | 2000 | 0.0 | 0.0 | 0.0 |
| Steam turbine | 0.90 | 6400 | 1.3 | 0.0 | -0.2 |
| Boiler | 0.89 | 4150 | 8.1 | 0.1 | 0.1 |
| Combined cycle boiler | 0.90 | 3000 | 0.2 | 0.0 | 0.0 |
| Nuclear reactor | 0.94 | 17500 | 0.0 | 0.0 | 0.0 |

1) 0.0 means no impact
2) the corresponding value of the objective in the Reference Run: 185277 Mton $CO_2$; 30637 bln € system costs
-0.8 means 0.8 × 1000 = 800 Mton $CO_2$ less, 0.3 means
-0.3 × 1000 = 300 bln € less costs

*Profitability*

As can be seen from Table 5.10, the impact on profitability in general is negligible: only the boiler, gasifier and to a lesser extent also the steam turbine are 'profitable' in terms of market impact. For every € invested in 'boiler R&D' over 7 € extra will be earned. Correspondingly, for every € invested in 'gasifier R&D' over 5 € extra will be earned. It must be kept in mind though, that this is not a linear relationship. Results are dependent on the absolute level of the shock applied (i.e. on the progress ratio improvement that is achieved).

It is remarkable that according to these results, renewable technologies (like Solar PV, Wind and Hydro) seem not to be favoured from an R&D policy point of view. This even holds for biomass applications, for although R&D investments in gasifiers does pay off, the majority of the gasifiers are installed in integrated coal gasification power plants.

### *$CO_2$ emissions*

As with profitability, the impact on $CO_2$ limitation in general is negligible. This can of course be explained by the equally negligible impacts on profitability: if a technology is not implemented (like e.g. in the cases with solar PV modules and wind turbines) emissions won't be effected. In the case of gasifiers, every € invested in gasifier R&D leads to 0.8 Mton of extra $CO_2$ emission reduction. In absolute terms however, this corresponds to 788 Mtons only (i.e. less than 0.5% of the Reference Run emissions). In the case of boilers, R&D shocks lead to an *increase* of $CO_2$ emissions, so here the effect of R&D shocks is a negative one (though in absolute terms again the effects are marginal, i.e. 0.3% or less). Negative effects (or increasing emissions) are explicable in cases where conventional, fossil fuel based technologies (like boilers) are implemented. The fact that the effects of R&D shocks are negligible in all cases (i.e. also when renewable technologies are stimulated) clearly demonstrates that the carbon values as applied (i.e. 15 €/ton $CO_2$ till 2010 and 33 €/ton $CO_2$ till 2030) are no stimulus for $CO_2$ reduction. As was stated earlier, this confirms the results of former runs with the EU MARKAL model for different projects, where only at carbon values above 100 €/ton $CO_2$ emissions are reduced (see e.g. Gielen et al., 2000).

Once again, it is mentioned here that in absolute terms, the total emissions stay more or less constant. The change in cumulative $CO_2$ emissions (that result from a 'shock' run) is in all cases smaller than (plus or minus) 0.5% when compared to the Reference Run. The corresponding amount of $CO_2$ varies from 508 Mton (in case of boilers) to -788 Mton (in case of gasifiers).

### *Costs to the consumer*

As stated above, the value of the energy system costs is used here as a proxy for the costs to the consumer. As can be seen from Table 5.10, again the impact on cost reductions to the consumer in general is negligible and in non of the cases. The R&D investment is 'profitable' in terms of 'costs to consumer impact': for every € invested in 'technology R&D' either nothing or less than 1 € will be earned (i.e. costs are reduced). In the case of the boiler the costs to the consumer actually increase. A negative value in Table 5.10 corresponds to a reduction in costs when compared to the Reference run.

Table 5.11 *Objectives measurement Soft landing + Shocks (1-10)*

| Case i.e. 'shock' on technology | New PR (in case) | R&D Shock M€ | Impact on market ('profitability') M€/M€ | Impact on $CO_2$ [1)] limitation objective Mton $CO_2$/M€ | Impact on cost [1)] reductions to the consumer M€/M€ |
|---|---|---|---|---|---|
| Solar PV modules | 0.792 | 355000 | 0.0 | 0.0 | 0.0 |
| Wind turbine | 0.85 | 22000 | 0.0 | 0.0 | 0.0 |
| Fuel cell | 0.791 | 100000 | 0.0 | 0.0 | 0.0 |
| Gasifier | 0.85 | 1000 | 12.2 | 0.0 | -0.7 |
| Gas turbine | 0.82 | 5000 | 0.2 | 0.0 | 0.0 |
| Hydro turbine | 0.94 | 2000 | 0.1 | 0.0 | 0.1 |
| Steam turbine | 0.90 | 6400 | 0.0 | 0.0 | 0.0 |
| Boiler | 0.89 | 4150 | 0.3 | 0.0 | -0.1 |
| Combined cycle boiler | 0.90 | 3000 | 0.4 | 0.0 | 0.1 |
| Nuclear reactor | 0.94 | 17500 | 0.0 | 0.0 | 0.0 |

1) 0.0 means no impact, the corresponding value of the objective in the Soft Landing: 160351 Mton $CO_2$

*Profitability*
As can be seen from Table 5.11, the impact on profitability in general is negligible: now only the gasifier is 'profitable' in terms of market impact: for every € invested in 'gasifier R&D' over 11 € extra will be earned. Unlike in the Reference Run plus shocks, here the gasifier is the *only* profitable technology. Again boilers and turbines have a small positive effect in terms of profitability, but the invested € won't be paid back.

*$CO_2$ emissions*
In terms of $CO_2$ limitation, in all cases the R&D shocks have no effect on the $CO_2$ emissions. This can be explained by the fact that in this case (i.e. Soft Landing scenario) maximum $CO_2$ emission levels (based on the Kyoto target) are set, which the model has to accomplish (see also Table 5.8).

*Costs to the consumer*
As can be seen from Table 5.11, again the impact on cost reductions to the consumer in general is negligible and in none of the cases, the R&D investment is 'profitable' in terms of 'costs to consumer impact': for every € invested in 'technology R&D' either nothing or less than 1 € will be earned (i.e. costs are reduced). In the cases of hydro turbines and combined cycle boilers the costs to the consumer actually increase. A negative value in Table 5.11 corresponds to a reduction in costs when compared to the Reference run.

*Reference Run vs. Soft Landing*
By comparing Tables 5.10 and 5.11, it is evident that in the Soft Landing Scenario the cumulative emissions are significantly lower than in the Reference Run (difference is 13%). However, this decrease is realized at significantly higher system costs (of 36 billion €, corresponding to 720 M€/year).
Just as an illustration, $CO_2$ emissions for both runs (Reference Run and Soft Landing) are presented graphically in Figure 5.1. The figure includes the shock runs for Solar PV, but results are not very different for the other cases.

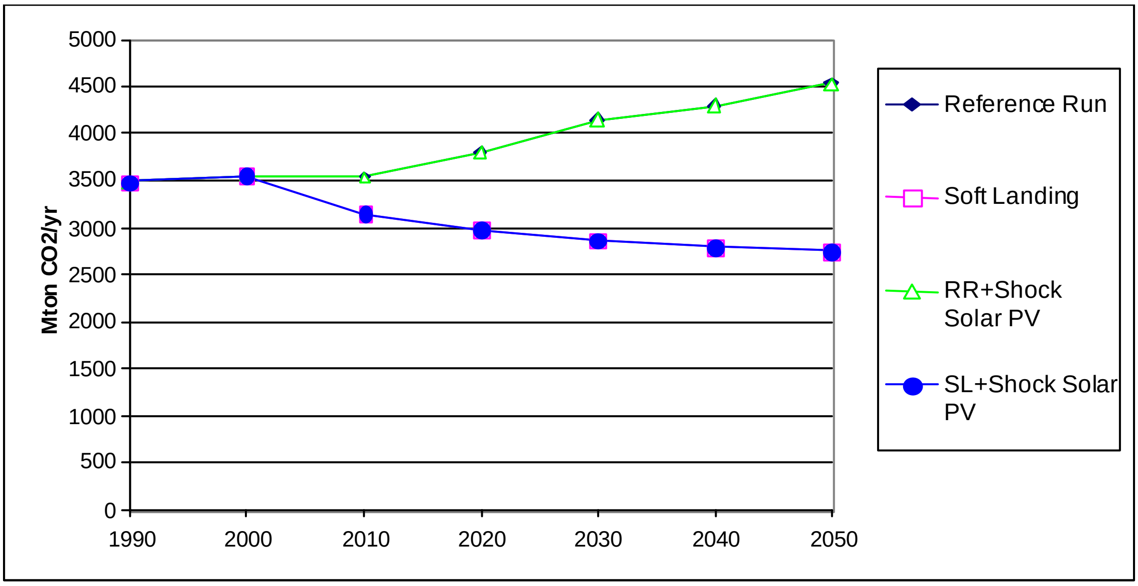


Figure 5.1 *$CO_2$ emissions in Reference Run and Soft Landing scenario (incl. shock Solar PV)*

### 5.5.2 Other results

Below follows a short overview of other results.

*Reference Run + Shocks 1-10 (set 1)*

Table 5.12 gives the cumulative capacities installed of key technologies, both in the Reference Run and Shock Runs. Correspondingly, Table 5.13 gives the specific costs of key technologies.

Table 5.12 *Cumulative capacities installed (2050) as % of maximum [GW]*

| Case | Maximum | Reference Run | Shock Run | Δ |
|---|---|---|---|---|
| Solar PV modules | 1000 | 0.6 | 0.6 | 0 |
| Wind turbine | 1000 | 24.9 | 24.9 | 0 |
| Fuel cell | 1000 | 0.0 | 0.0 | 0 |
| Gasifier | 1000 | 45.4 | 47.7 | 2.4 |
| Gas turbine | 1000 | 59.1 | 59.1 | 0 |
| Hydro turbine | 1000 | 18.9 | 18.9 | 0 |
| Steam turbine | 1500 | 41.3 | 59.1 | 17.8 |
| Boiler | 1000 | 16.5 | 65.8 | 49.3 |
| Combined cycle boiler | 1000 | 28.5 | 28.5 | 0 |
| Nuclear reactor | 1000 | 6.2 | 6.2 | 0 |

Table 5.13 *Specific costs Reference Run (2050) in [€95/kW]*

| Case | Initial costs 1990 | Reference Run | Shock Run | % of $\text{costs}_{\text{RefRun}}$ | Δ |
|---|---|---|---|---|---|
| Solar PV modules | 7500 | 2127 | 1900 | 89 | -228 |
| Wind turbine | 1400 | 440 | 245 | 56 | -195 |
| Fuel cell | 2650 | 1217 | 1193 | 98 | -24 |
| Gasifier | 800 | 310 | 177 | 57 | -133 |
| Gas turbine | 450 | 243 | 189 | 78 | -54 |
| Hydro turbine | 300 | 298 | 256 | 86 | -41 |
| Steam turbine | 300 | 294 | 243 | 83 | -51 |
| Boiler | 510 | 505 | 388 | 77 | -117 |
| Combined cycle boiler | 500 | 334 | 217 | 65 | -117 |
| Nuclear reactor | 1940 | 1919 | 1869 | 97 | -50 |

As can be seen from Table 5.13, an R&D impulse in all cases has a positive (in the sense that the costs decrease) impact on the specific costs of the technology. However this does not lead by definition to more installed capacity as is illustrated by Table 5.12. For example, Solar PV modules reach a cost reduction of 11% (compared to costs in the Reference run) but are not installed more. The reason for this is the competition from other technologies: in earlier runs (i.e. when less clusters of learning technologies were implemented) Solar PV as well as Fuel Cells was installed (we will come back to this later in Section 5.5.3). From this result it can be concluded that the number of learning technologies is important.

Boilers, gasifiers and steam turbines are 'winning' technologies in R&D shock runs. As was already concluded in Section 5.5.1, renewable technologies do not seem to benefit from the R&D shocks applied (in terms of extra installed capacity). This is largely explained by the low carbon values (i.e. low carbon taxes and shadow prices) applied. Higher carbon taxes could have had a more beneficial impact on the penetration of renewable technologies.

Just as an illustration, Figures 5.2, 5.4 and 5.6 give cumulative capacities installed (1990-2050) for wind turbines, gasifiers and combined cycle boilers in both sets of runs. Correspondingly, Figures 5.3, 5.5 to 5.7 give the specific technology costs.

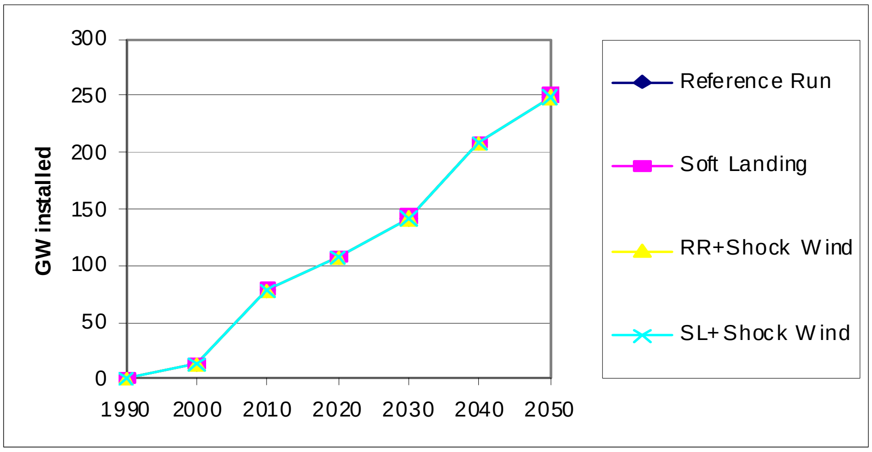


Figure 5.2 *Cumulative capacities of wind turbines*

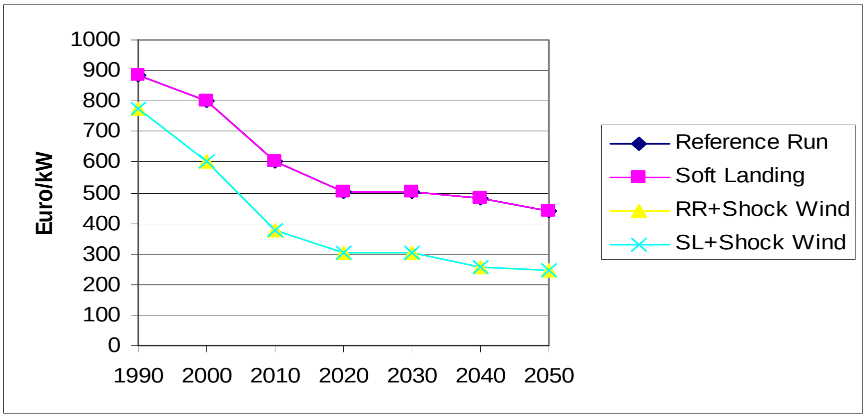


Figure 5.3 *Specific costs of wind turbines*

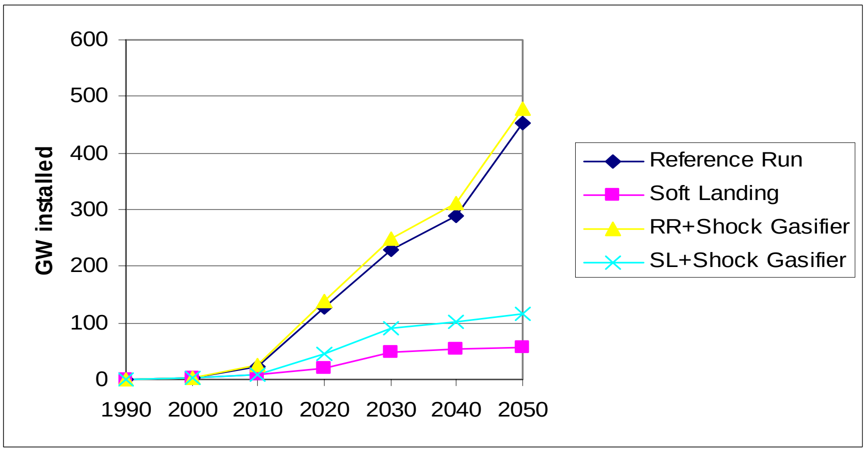


Figure 5.4 *Cumulative capacities of gasifiers*

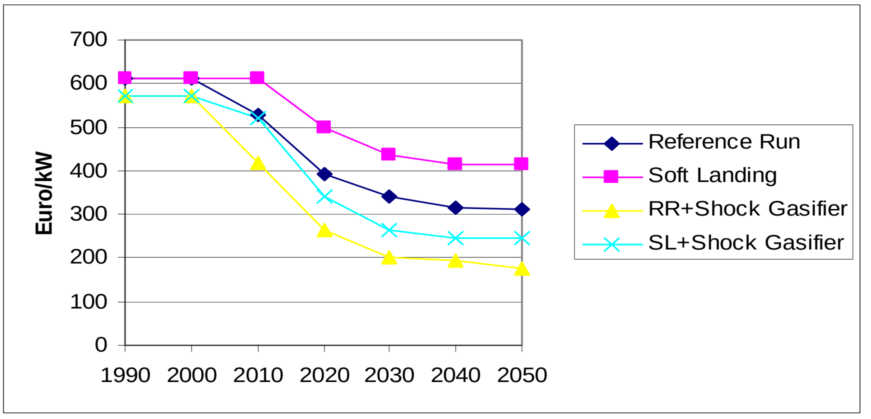


Figure 5.5 *Specific costs of gasifiers*

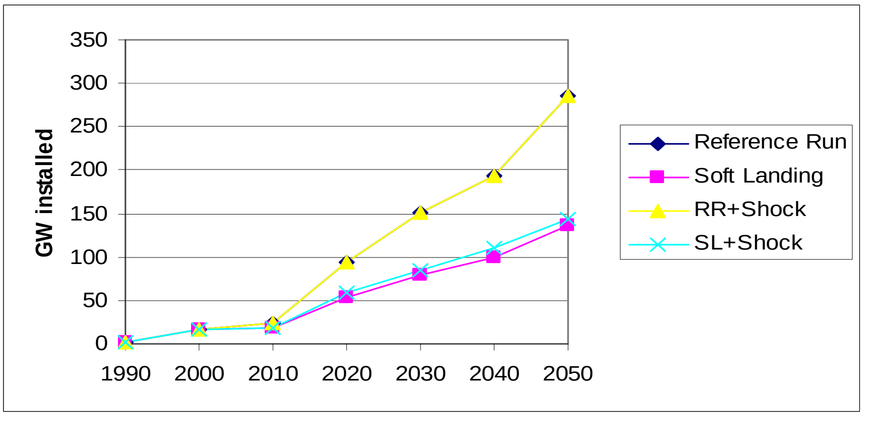


Figure 5.6 *Cumulative capacities of combined cycle boilers*

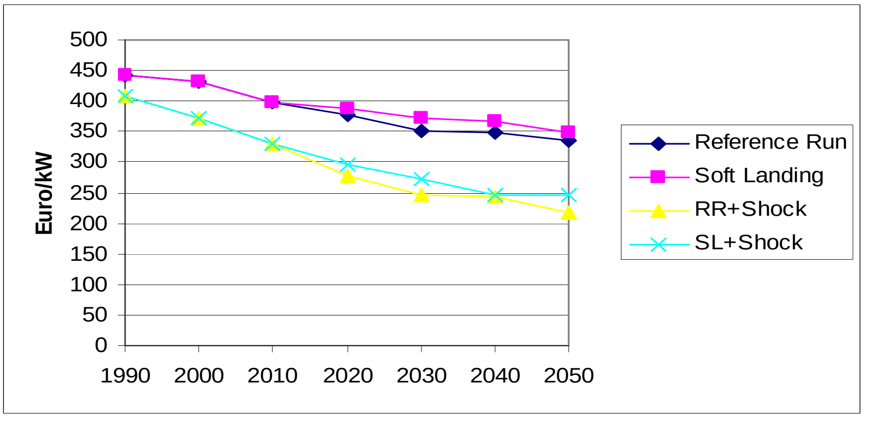


Figure 5.7 *Specific costs of combined cycle boilers*

Table 5.14 shows the energy system costs in the Reference and Shock runs. A negative value in the column 'Difference' means that the system costs are lower in the Shock run when compared to the Reference Run. As can be seen from Table 5.14, in every case the costs in the Shock runs actually are lower than in the Reference Run. The last column 'Δ Total costs' adds the absolute level of the shock applied to the cost difference calculated. Calculated like this, we conclude that in 6 out of 10 cases the investment of the R&D shock may be earned back by the decrease in energy system costs.

Table 5.14 *Energy system costs (discounted 2050) Reference Run Shocks [all in M€]*

| Case | Costs | Difference | Shock | Δ Total costs |
|---|---|---|---|---|
| Reference Run | 54978519 | - | - | - |
| Solar PV modules | 54977500 | -1018 | 355000 | 353982 |
| Wind turbine | 54962078 | -16441 | 22000 | 5559 |
| Fuel cell | 54978516 | -3 | 100000 | 99997 |
| Gasifier | 54966418 | -12100 | 1000 | -11100 |
| Gas turbine | 54972475 | -6044 | 5000 | -1044 |
| Hydro turbine | 54974734 | -3784 | 2000 | -1784 |
| Steam turbine | 54970688 | -7831 | 6400 | -1431 |
| Boiler | 54967257 | -11261 | 4150 | -7111 |
| Combined cycle boiler | 54972194 | -6324 | 3000 | -3324 |
| Nuclear reactor | 54977949 | -569 | 17500 | 16931 |

### *Soft Landing + Shocks 1-10 (set 2)*

Table 5.15 gives the cumulative capacities installed of key technologies, both in the Reference Run and Shock Runs. Correspondingly, Table 5.16 gives the specific costs of key technologies.

Table 5.15 *Cumulative capacities installed (2050) as % of maximum [GW]*

| Case | Maximum | Soft Landing Run | Shock Run | Δ |
|---|---|---|---|---|
| Solar PV modules | 1000 | 0.6 | 0.6 | 0 |
| Wind turbine | 1000 | 24.9 | 24.9 | 0 |
| Fuel cell | 1000 | 0.0 | 0.0 | 0 |
| Gasifier | 1000 | 5.6 | 11.7 | 6.0 |
| Gas turbine | 1000 | 36.7 | 37.8 | 1.1 |
| Hydro turbine | 1000 | 49.8 | 50.2 | 0.4 |
| Steam turbine | 1500 | 35.8 | 36.4 | 0.5 |
| Boiler | 1000 | 14.2 | 15.6 | 1.4 |
| Combined cycle boiler | 1000 | 13.6 | 14.2 | 0.6 |
| Nuclear reactor | 1000 | 17.7 | 17.7 | 0 |

Table 5.16 *Specific costs Soft Landing Run (2050) in [€95/kW]*

| Case | Initial $costs_{1990}$ | Soft Landing Run | Shock Run | % of $costs_{SoftLand}$ | Δ |
|---|---|---|---|---|---|
| Solar PV modules | 7500 | 2127 | 1900 | 89 | -228 |
| Wind turbine | 1400 | 440 | 245 | 56 | -195 |
| Fuel cell | 2650 | 1217 | 1193 | 98 | -24 |
| Gasifier | 800 | 413 | 244 | 59 | -169 |
| Gas turbine | 450 | 283 | 240 | 85 | -43 |
| Hydro turbine | 300 | 296 | 226 | 76 | -70 |
| Steam turbine | 300 | 294 | 243 | 82 | -52 |
| Boiler | 510 | 505 | 458 | 91 | -47 |
| Combined cycle boiler | 500 | 349 | 247 | 71 | -102 |
| Nuclear reactor | 1940 | 1919 | 1812 | 94 | -108 |

As far as the relation between prices decreases and installed capacity, the results for the Soft Landing Scenario are comparable with these of the ‘Reference’ Scenario (Tables 5.12 and 5.13). However, other technologies are now favoured, though the effects (in terms of extra capacity installed) are less pronounced as in the Reference Run. When comparing the Reference Run and Soft Landing Run, the capacities of gasifiers, gas turbines and combined cycle boilers decrease. This is explained by the maximum $CO_2$ emission levels set which the model has to accomplish (see also Table 5.8). For the same reason the model now ‘chooses’ Hydro and Nuclear Power instead.

In general, the impact of the R&D shocks - in terms of additional installed capacity - is less significant than in the 'Reference Scenario'. This can be explained by the fact, that already without the shock, a lot of technologies with high learning potential are installed.

Table 5.17 shows the energy system costs in the Soft Landing and Shock runs. A negative value in the column 'Difference' means that the system costs are lower in the Shock run when compared to the Reference Run. As can be seen from Table 5.17, in every case the costs in the Shock runs actually are lower than in the Soft Landing Run. The last column 'Δ Total costs' adds the absolute level of the shock applied to the cost difference calculated. Calculated like this, we conclude that in 4 out of 10 cases the investment of the R&D shock will be earned back by the decrease in energy system costs. When compared to the Reference Run plus shocks, in general the cost differences are lower (with the exception of hydro turbines and nuclear reactors). After addition of the shock level, the technologies that are profitable are the same as in the Reference Run, though in the cases of gas and steam turbines the R&D shocks are not earned back any more in the Soft Landing runs.

Table 5.17 *Energy system costs (discounted 2050) Soft Landing Run + Shocks [all in M€]*

| Case | Costs | Difference | Shock | Δ Total costs |
|---|---|---|---|---|
| Soft Landing | 55092754 | - | - | - |
| Solar PV modules | 55091736 | -1018 | 355000 | 353982 |
| Wind turbine | 55076314 | -16441 | 22000 | 5559 |
| Fuel cell | 55092751 | -3 | 100000 | 99997 |
| Gasifier | 55089715 | -3039 | 1000 | -2039 |
| Gas turbine | 55088785 | -3970 | 5000 | 1030 |
| Hydro turbine | 55085270 | -7484 | 2000 | -5484 |
| Steam turbine | 55086848 | -5907 | 6400 | 493 |
| Boiler | 55086845 | -5909 | 4150 | -1759 |
| Combined cycle boiler | 55089419 | -3335 | 3000 | -335 |
| Nuclear reactor | 55089755 | -3000 | 17500 | 14500 |

### 5.5.3 Clarification of some results

*Lock out effects*

As stated in Section 5.5.2, technologies like Solar PV and Fuel Cells are not installed more despite cost reductions achieved thanks to the R&D impulse (11% in the case of Solar PV). The explanation for this somewhat contradictory result is the competition from other technologies. This can be concluded based on earlier runs, i.e. when less clusters of learning technologies were implemented. At that time, Solar PV modules as well as Fuel Cells were installed. As an illustration, figure 5.8 shows the former results for Solar PV (relevant are the data labelled as SL and SL R&D).

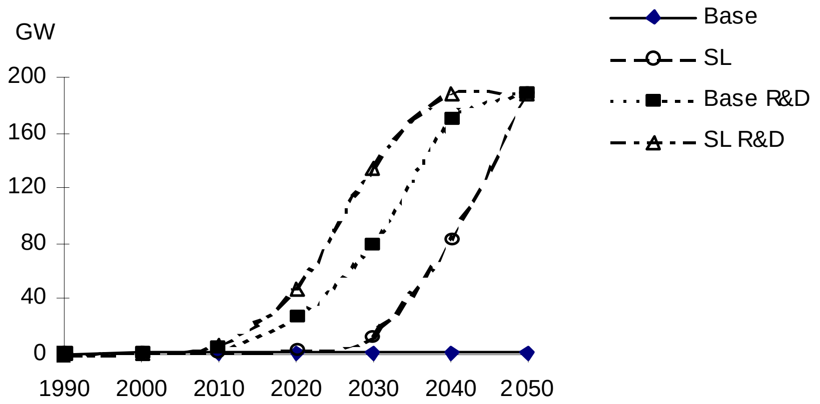


Figure 5.8 *Capacity of Solar PV modules after implementation of 2 clusters*

Looking at Figure 5.8, it is very clear that the capacity of Solar PV modules installed (~ 200 GW) is significantly higher than in the latest runs (i.e. after implementation of 10 clusters, see also Tables 5.12 and 5.15) where the capacity is fixed on the lower bound applied. From figure 5.8, it is concluded that the number of learning technologies is important.

### *Influence of Progress Ratio chosen*

As a sort of sensitivity analysis, the progress ratio of Solar PV modules was varied in the Soft Landing scenario. The results in terms of cumulative capacity installed are presented in Table 5.18. This clearly shows the importance of the learning potentials and it may be that the progress ratio in case of Solar PV modules has been assumed too pessimistic.

Table 5.18 *Cumulative capacity [GW] of Solar PV, Soft Landing with varying progress ratios*

| | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|
| PR = 0.82 | 0.1 | 0.95 | 3.1 | 3.1 | 3.95 | 6.1 | 6.1 |
| PR = 0.792 | 0.1 | 0.95 | 3.1 | 3.1 | 3.95 | 6.1 | 6.1 |
| PR = 0.70 | 0.1 | 0.95 | 3.1 | 3.4 | 3.95 | 6.1 | 6.4 |
| PR = 0.66 | 0.1 | 0.95 | 3.1 | 3.5 | 7.15 | 96 | 246 |

### *Influence of Upper Bounds chosen*

After former runs, upper capacity bounds for wind turbines were installed on the basis of the latest DG TREN scenarios (LREM, 2002). As results, wind turbines become less attractive.

## 5.6 Conclusions and Recommendations

The fact that in the Reference Run calculations (i.e. with carbon values of 15 €/ton $CO_2$ till 2010 and 33 €/ton $CO_2$ till 2030), the effects of R&D 'shocks' on $CO_2$ emissions are negligible in all cases (i.e. also when renewable technologies are stimulated), demonstrates that the carbon values as applied are no stimulus for $CO_2$ reduction. This confirms the results of other studies with the MARKAL Western Europe (see e.g. Gielen et al., 2000).

In the Soft Landing Scenario the cumulative emissions are significantly lower than in the Reference Run (difference is 13%). However, this decrease is realised at significantly higher system costs (of 114 billion €).

The impact of the R&D shocks - in terms of additional installed capacity - is less significant in the 'Soft Landing' than in the 'Reference' scenario. This is because of the fact that already without the shock, a lot of technologies with high learning potential are installed. This is necessary in order to accomplish the maximum $CO_2$ emission levels that are set in the Soft Landing scenario.

R&D shocks generally have a positive (i.e. price lowering) impact on the specific costs of the technology. However, this does not by definition lead to more install capacity (e.g. Solar PV and Fuel Cells). The reason for this is the competition from other technologies. It should be kept in mind that both Solar PV and Fuel Cells were attractive in previous MARKAL SAPIENT calculations when only 6 clusters were implemented (so for instance boilers and steam turbines were not yet a learning or key technology). After the addition of the gasifier cluster, Solar PV and Fuel Cells seem to be effectively locked out because implementation of gasifiers becomes more cost effective due to the learning process. This shows the importance of a proper and balanced identification of clusters of learning technologies and the various learning potentials. The learning potential of the more conventional technologies may now be assumed to be too optimistic. It is recommended to review the resulting floor costs of these technologies in more detail: can such cost reductions really be achieved?

On the other hand, the learning potentials of renewable technologies like Solar PV modules may be assumed too pessimistic. A quick sensitivity check has shown that with a (historically very low) progress ratio of 0.66 solar PV is implemented, even in the case of 10 clusters of learning technologies.

The indirect approach to 2FLC and the used R&D statistics lead to only marginal changes in progress ratios. So, even beforehand, little impact was to be expected, certainly for the renewable technologies. Comparison with the MARKAL TEEM experiments learns that for instance substantially lower progress ratios and/or a more stringent $CO_2$ policy can make technologies like Solar PV cost-effective. This demonstrates that model assumptions are extremely important for the results.

Given the previous conclusions above, one should be very careful to derive very technology specific conclusions from these MARKAL calculations. With other (equally probable or plausible) assumptions, technologies like solar PV and fuel cells could become attractive as well.

The MARKAL SAPIENT results indicate that R&D policy can never stand on its own. R&D can certainly help to reduce specific technology costs but to get technologies into the market additional policy measures are needed. Such market policy measures could be upper emission quota or minimum quantity obligations for specific technologies. The combination of the two (a combination of technology push and market pull) might lead to more socially desired outcomes.

# 6. SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

- For the first time a large number of learning technologies have been successfully implemented in a large-scale integrated energy model. With 10 learning key components and about 60 technologies affected by learning we have been able to keep solutions times within realistic limits.

- Uncertainty is an important element in the use of energy models for energy forecasting. With the use of a Monte Carlo analysis the most sensitive parameters leading to object values can be determined as well as their impact weight. The results of an uncertainty analysis in progress ratios of wind turbines and comparing this to the impact of R&D on the progress ratio indicate that the uncertainty in the progress ratio is more important than the estimated effect of R&D-expenditures on the progress ratio. This finding supports the idea that it is more important to obtain good data for the one-factor learning curve parameters, than to introduce a more complex two-factor learning curve (either indirect or direct).

- For several reasons, elaborated in Chapter 2, ECN has chosen to explore an alternative approach to the two-factor learning curve, to model the impact of R&D on technology learning. This alternative approach is to assume a relationship between the R&D-intensity of a technology (the percentage of R&D-expenditure divided by the sum of the R&D-expenditure and the total sales over a given period) and its progress ratio. Based on three observations (fuel cells, wind turbines and solar PV) a linear relation between the two parameters was assumed. This exercise suggested a learning-by-doing progress ratio (learning without any R&D) of about 95%.

- Applying 'R&D-shocks' to technologies selected using the R&D-intensity approach led to several insights. In the first place, it appeared that the scenario conditions (especially with regard to expected carbon prices) had much more impact on the model outcomes than enhancing the progress ratio of specific technologies as a result of additional R&D-expenditures. These results indicate that R&D-policy can never stand on its own. R&D can certainly help to reduce specific technology costs, but to get technologies into the market, deployment policies and external cost pricing are necessary as well. The fact that new technologies have to compete with more conventional technologies that are also able to learn ('moving targets') makes it much more difficult for them to enter the market.

- Evaluating the R&D-intensity approach to model technology learning, one can say that the positive news is that it is a feasible approach for large integral energy models. However, several of the assumptions behind this model need to be checked. The data on which this model is based are very scarce: only three technologies (wind turbines, fuel cells and solar PV) that are rather new to the energy sector. A characteristic of these technologies is that a very important part of R&D-spending is public R&D. However, it can be expected that if these technologies enter the market more substantially, there will be a shift from public to private R&D, meaning that the assumption that public R&D-spending is representative for total R&D-spending doesn't hold anymore. Also it is difficult to get enough data to assess the R&D-intensity over a certain period. For several technologies one would have to go to analyse large industrial sectors outside the energy system (e.g. the aviation industry for gas turbines, or the ICT-industry for cost reduction of electronics).

- Much of the theoretical and data problems mentioned above are shared with other approaches to model R&D-spending on technology learning, such as the two-factor learning curve. This means that one should be careful at this moment in drawing robust policy conclusions from the exercises done in the SAPIENT project. Exploring different approaches (2FLC and R&D-intensity) the SAPIENT energy modellers learned a lot. To continue further riding of our own experience curve combinations of these approaches or new approaches will have to be explored in the future.

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# ANNEX A: OVERVIEW OF TECHNOLOGIES CONSIDERED

Table A.1 *Technologies in MARKAL*

| Code | Corresponding technology |
|---|---|
| BD1 | Lignine boiler large industrial cog. |
| BD2 | Lignine gasifier large industrial cog. |
| BE1 | Wood gasification small industrial cog. |
| BE2 | Wood gasification CC power plant |
| BE3 | Biomass gasifierdedicated CC (NH) |
| BE4 | Biomass gasifier SOFC |
| BE5 | Co-firing wood chips in coal fired plant |
| BE6 | IGCC with co-gasification of biomass |
| BE7 | Biomass gas turbine plant |
| BE8 | Biomass gasifierdedicated CC (NH) STW |
| BE9 | Biomass gasifier FT-fuel/elec. co-prod |
| BI4 | HTU oil/CC power plant |
| EC2 | Existing pulverised coal fired p.p. |
| EC3 | Existing lignite fired power plant |
| EC4 | New pulverised coal fired power plant |
| EC5 | Integrated coal gasification p.p. |
| EC6 | New lignite fired power plant |
| EC7 | Integrated lignite fired power plant |
| EC8 | Integrated Coal Gasification SOFC plant |
| ECA | Coal FBC CHP plant |
| ED0 | Existing oil fired power plant |
| ED1 | New oil fired power plant |
| ED2 | Oil gasification combined cycle p.p. |
| EG0 | Existing gas fired power plant |
| EG1 | Gas turbine peaking plant |
| EG2 | Existing CC power plant |
| EG3 | New CC power plant |
| EG4 | Combined cycle SOFC power plant |
| EGA | Existing gas turbine CHP plant |
| EGB | Existing CC CHP plant |
| EGD | New gas turbine CHP plant |
| EGE | New CC CHP plant |
| EGG | HERON SOFC total energy for H, C and A |
| EH0 | Medium and high head hydro |
| EH1 | Low head hydro |
| EH2 | Hydro pumped storage |
| EH3 | Archimedes Wave Swing |
| EH5 | Hydro Iceland for Aluminium smelters |
| EI1 | Waste to energy plant (incinerator) |
| EI2 | Waste to energy plant (Lurgi gasifier) |
| EI3 | Waste to energy plant (Gibros PEC) (PEC = Product and Energy Plant) |
| EN0 | LWR power plant |
| ES1 | Solar PV in Northern Europe |
| ES2 | Solar PV roofs southern ESP, IT, GR |

| Code | Corresponding technology |
|---|---|
| ES3 | Solar PV in Central Europe |
| ES4 | Solar PV roofs/barren land cent. ESP, IT |
| ES5 | Solar PV: import from North Africa |
| EW4 | Large onshore wind turbine - inland |
| EW5 | Large onshore wind turbine - shore |
| EW6 | Off-shore wind turbine - near shore |
| EW7 | Off-shore wind turbine - off shore |
| EXA | Steam turbine industry |
| T05 | Fuel Cell car with MF and RB (RB = Regenerative braking) |
| T0F | Fuel Cell car with MF (MF = Modified frame) |
| T15 | Fuel Cell van with MF and RB |
| T1F | Fuel Cell van with MF |
| T23 | Fuel Cell Truck with MF and RB |
| T2F | Fuel Cell Truck with MF |
| T3F | Fuel Cell bus with MF and RB |

Table A.2 *Technologies in POLES*

| Code | Corresponding technology |
|---|---|
| HYD | Large Hydro |
| NUC | Nuclear LWR |
| NND | New Nuclear Design (Evolutionary type) |
| LCT | Lignite Conventional Technology |
| CCT | Coal Conventional Technology |
| PFC | Pulverized Fuel Supercritical Coal |
| ICG | Integrated Coal Gasification |
| ACT | Advanced Thermodynamic Cycle |
| OCT | Oil Conventional Technology |
| OGT | Oil in GTCC |
| GCT | Gas Conventional Technology |
| GGC | Gas in GTCC |
| CHP | CHP |
| SHY | Small hydro |
| WND | Wind |
| SPP | Solar Thermal Power Plant |
| DPV | Decentralised PV (building integrated) |
| RPV | Rural PV (electrification in LDCs) |
| BF2 | Electricity production from waste |
| BGT | Biomass gasification + GTCC |
| FCV | Fuel Cell Vehicle (PEMFC) (PEM = Proton Exchange Membrane) |
| SFC | Solid oxide FC |
| MFC | Molten Carbonate fuel cells |

# ANNEX B: SUMMARY OF COUPLING FACTORS USED

Table B.1 *Selected MARKAL technologies/processes*

| Description Key technologies → | ESK | WTK | FCK | GFK | GTK | HYK | STK | BOK | CCK | NUK |
|---|---|---|---|---|---|---|---|---|---|---|
| Lignine boilerlarge industrial cog. | | | | | | | 1.0 | 1.0 | | |
| Lignine gasifierlarge industrial cog. | | | | 1.0 | 0.6 | | 0.4 | | | |
| Wood gasificationsmall industrial cog. | | | | 1.0 | 0.6 | | 0.4 | | | |
| Wood gasificationCC power plant | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Biomass gasifierdedicated CC (NH) | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Biomass gasifierSOFC | | | 0.6 | 1.0 | 0.2 | | 0.2 | | 0.2 | |
| Co-firing wood chips in coal fired plant | | | | | | | 1.0 | 1.0 | | |
| IGCC with co-gasification of biomass | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Biomass gas turbine plant | | | | 1.0 | 1.0 | | | | | |
| Biomass gasifierdedicated CC (NH) STW | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Biomass gasifier FT-fuel/ele co-prod | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| HTU oil/CC power plant | | | | | 0.67 | | 0.33 | | 0.33 | |
| Existing pulverised coal fired p.p. | | | | | | | 1.0 | 1.0 | | |
| Existing lignite fired power plant | | | | | | | 1.0 | 1.0 | | |
| New pulverised coal fired power plant | | | | | | | 1.0 | 1.0 | | |
| Integrated coal gasification p.p. | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| New lignite fired power plant | | | | | | | 1.0 | 1.0 | | |
| Integrated lignite fired power plant | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Integrated Coal Gasification SOFC plant | | | 0.6 | 1.0 | 0.2 | | 0.2 | | 0.2 | |
| Coal FBC CHP plant | | | | | | | 1.0 | | | |
| Existing oil fired power plant | | | | | | | 1.0 | 1.0 | | |
| New oil fired power plant | | | | | | | 1.0 | 1.0 | | |
| Oil gasification combined cycle p.p. | | | | 1.0 | 0.6 | | 0.4 | | 0.4 | |
| Existing gas fired power plant | | | | | | | 1.0 | 1.0 | | |
| Gas turbine peaking plant | | | | | 1.0 | | | | | |
| Existing CC power plant | | | | | 0.67 | | 0.33 | | 0.33 | |
| New CC power plant | | | | | 0.67 | | 0.33 | | 0.33 | |
| Combined cycle SOFC power plant | | | 0.8 | | 0.12 | | 0.08 | | 0.08 | |
| Existing gas turbine CHP plant | | | | | 1.0 | | | | | |
| Existing CC CHP plant | | | | | 0.67 | | 0.33 | | 0.33 | |
| New gas turbine CHP plant | | | | | 1.0 | | | | | |
| New CC CHP plant | | | | | 0.67 | | 0.33 | | 0.33 | |
| HERON SOFC total energy for H, C and A | | | 0.8 | | 0.2 | | | | | |
| Medium and high head hydro | | | | | | 1.0 | | | | |
| Low head hydro | | | | | | 1.0 | | | | |
| Hydro pumped storage | | | | | | 1.0 | | | | |
| Archimedes Wave Swing | | | | | | 1.0 | | | | |
| Hydro Iceland for Aluminium smelters | | | | | | 1.0 | | | | |
| Waste to energy plant (incinerator) | | | | | | | | 1.0 | | |
| Waste to energy plant (Lurgi gasifier) | | | | 1.0 | | | | 1.0 | | |
| Waste to energy plant (Gibros PEC) | | | | 1.0 | | | | 1.0 | | |
| LWR power plant | | | | | | | | 1.0 | | 1.0 |
| Solar PV in Northern Europe | 1.0 | | | | | | | | | |
| Solar PV roofs southern ESP, IT, GR | 1.0 | | | | | | | | | |
| Solar PV in Central Europe | 1.0 | | | | | | | | | |
| Solar PV roofs/barren land cent. ESP, IT | 1.0 | | | | | | | | | |
| Solar PV: import from North Africa | 1.0 | | | | | | | | | |
| Large onshore wind turbine - inland | | 1.0 | | | | | | | | |
| Large onshore wind turbine - shore | | 1.0 | | | | | | | | |

| Description Key technologies → | ESK | WTK | FCK | GFK | GTK | HYK | STK | BOK | CCK | NUK |
|---|---|---|---|---|---|---|---|---|---|---|
| Off-shore wind turbine - near shore | | 1.0 | | | | | | | | |
| Off-shore wind turbine - off shore | | 1.0 | | | | | | | | |
| Steam turbine industry | | | | | | | 1.0 | 1.0 | | |
| Fuel Cell car with MF and RB | | | 4.0 | | | | | | | |
| Fuel Cell car with MF | | | 4.0 | | | | | | | |
| Fuel Cell van with MF and RB | | | 2.2 | | | | | | | |
| Fuel Cell van with MF | | | 2.2 | | | | | | | |
| Fuel Cell Truck with MF and RB | | | 0.74 | | | | | | | |
| Fuel Cell Truck with MF | | | 0.74 | | | | | | | |
| Fuel Cell bus with MF and RB | | | 1.18 | | | | | | | |

*) Because transport (demand) technologies have a special unit in the EU MARKAL model (PJ to the wheels rather than vehicle kilometers) and because of lifetime/replacement considerations of the fuel cell stacks, these coupling factors have calculated differently than for other technologies

# ANNEX C: OVERVIEW OF BOUNDS APPLIED

Table C.1 *Upper bounds on capacity in scenario NOREBNDS [GW]*

| Code | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| BE1.UP | Wood gasificationsmall industrial cog. | - | 10 | 12.14 | 14.29 | 16.43 | 18.57 | 20.71 |
| BE2.UP | Wood gasificationCC power plant | 0.1 | 0.55 | 1 | 13 | 25 | 25 | 25 |
| BE3.UP | Biomass gasifierdedicated CC (NH) | - | 2 | 8.5 | 15 | 15 | 15 | 15 |
| BE5.UP | Co-firing wood chips in coal fired pl. | - | 0.1 | 25 | 25 | 25 | 25 | 25 |
| BE6.UP | IGCC with co-gasification of biomass | - | 4 | 47 | 90 | - | - | - |
| BE7.UP | Biomass gas turbine plant | 5 | 15 | 25 | 25 | 25 | 25 | 25 |
| BE8.UP | Biom.gasifierdedicated CC (NH) STW | - | 2 | 6.33 | 10.67 | 15 | 15 | 15 |
| BE9.UP | Biomass gasifier FT-fuel/ele co-prod | - | 17.33 | 33.67 | 50 | 62.5 | 75 | 87.5 |
| BI4.UP | HTU oil/CC power plant | - | 0.1 | 1 | 13 | 25 | 25 | 25 |
| EC2.UP | Existing pulverised coal fired p.p. | 115.8 | 94.72 | 45.95 | 0.002 | 0.002 | 0.002 | 0.002 |
| EC3.UP | Existing lignite fired power plant | 38.7 | 25.56 | 14.34 | 0.002 | 0.002 | 0.002 | 0.002 |
| EC4.UP | New pulverised coal fired power plant | - | 14.68 | - | - | - | - | - |
| EC5.UP | Integrated coal gasification p.p. | - | 4 | 47 | 90 | - | - | - |
| EC6.UP | New lignite fired power plant | - | 4.36 | - | - | - | - | - |
| EC7.UP | Integrated lignite fired power plant | - | 1 | 15.5 | 30 | - | - | - |
| ECA.UP | Coal FBC CHP plant | 4.58 | 4.5 | - | - | - | - | - |
| ED2.UP | Oil gasification combined cycle p.p. | - | 1 | 15.5 | 30 | - | - | - |
| EG0.UP | Existing gas fired power plant | 43.41 | 44.86 | - | - | - | - | - |
| EG2.UP | Existing CC power plant | 1.7 | 1.31 | 0.91 | 0.456 | 0.002 | 0.002 | 0.002 |
| EG3.UP | New CC power plant | - | 36.31 | - | - | - | - | - |
| EGA.UP | Existing gas turbine CHP plant | 7.18 | 5.18 | 5.18 | 2.59 | - | - | - |
| EGB.UP | Existing CC CHP plant | 0.67 | 0.67 | 0.67 | - | - | - | - |
| EGC.UP | Exist. gas eng. gen. set for H, C and A | 0.98 | 0.98 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| EGD.UP | New gas turbine CHP plant | - | 13.59 | 24.34 | 25.12 | 25.9 | 25.9 | 25.9 |
| EGE.UP | New CC CHP plant | - | 6.83 | 7.5 | 7.68 | 7.85 | 7.85 | 7.85 |
| EGF.UP | New gas eng. gen. set for H, C and A | - | 12.11 | 21.2 | 21.63 | 22.05 | 22.05 | 22.05 |
| EI1.UP | Waste to energy plant (incinerator) | 0.565 | 1.98 | 2.93 | 3.99 | 5.14 | 6.32 | 7.23 |
| EN0.UP | LWR power plant | 118.4 | 126.7 | 126.7 | 126.7 | 107.7 | 107.7 | 107.7 |

Table C.2 *Overview upper bounds on investment in scenario NOREBNDS [GW]*

| Code | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| ED0.UP | Existing oil fired power plant | - | - | - | - | 0.001 | 0.001 | 0.001 |
| EGA.UP | Existing gas turbine CHP plant | - | - | - | - | 0.001 | 0.001 | 0.001 |
| EGB.UP | Existing CC CHP plant | - | - | - | 0.01 | 0.01 | 0.01 | 0.01 |
| EN0.UP | LWR power plant | 37.77 | 8.31 | 2.63 | 45.04 | 45.41 | 38.92 | 32.44 |

Table C.3 *Lower capacity bound solar PV in scenario NOREBNDS [GW]*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATSOLARLO | Total Solar PV (= ∑ES1-ES5) | 0 | 0 | 3 | 3 | 3 | 3 | 3 |

Table C.4 *Upper capacity bounds wind in scenario NOREBNDS [GW]*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATWTON | Total wind onshore (EW4+5) | 1 | 13 | 72 | 103 | 123 | 130 | 136 |
| RATWTOFF | Total wind offshore (EW6+7) | 0.09 | 0.5 | 6.5 | 57 | 103 | 135 | 148 |

Table C.5 *Lower capacity bound solar PV scenario NOREBNDS [GW]*

| Constraint | Description | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 |
|---|---|---|---|---|---|---|---|---|
| RATWTOFFLO | Total wind offshore (EW6+7) | 0 | 0 | 5 | 5 | 5 | 5 | 5 |

# ANNEX D: COMPARISON OF MODEL DATA

## D.1 Background to and purpose of this appendix

Good modelling requires at least two things. A good model structure and a reliable model data set. Both items have received considerable attention during the SAPIENT project. With regard to data the SAPIENT team has spent considerable time to get a reliable set of historical data on investment costs developments and R&D-expenditures. This was done primarily to estimate reliably learning-by-doing and learning-by-searching elasticity's for investment costs (the two-factor learning curve). However, large-scale models do still not always work in the ETL (Endogenous Technology Learning) mode and apart from this also other important data, apart from investment costs, do characterise a technology in the model databases.

There are many different possible causes if differences in outcomes between models occur. Perhaps two different classes of these causes can be distinguished. Either the model structure and assumptions are different, or the model data differ. The former cause is often subject of discussion. However, the latter cause might be as important. To get some feeling for how small or large differences in data currently are, the SAPIENT team decided to make a comparison of a small part of technology characterisation data that the models used in SAPIENT have in common.

How is this Annex structured? In Section D.2 an explanation will be given how the comparison will be made. This includes a description of what kind of data will be compared and also an explanation on some specifics of data in each model. In section D.3 the comparison will be made. For three technologies (wind, hydro and PV) we will look at investment costs, O&M costs (fixed and variable), estimated lifetime and estimated availability of the technologies considered. In section D.4 we will recapitulate the main conclusions and put forward some recommendations for future research activities. The main recommendation is that in the near future much more time should be spent on data acquisition, validation and convergence between the different models.

## D.2 How the comparison will be made

Input data of six different models have been compared. These models are PRIMES, POLES, MARKAL, MESSAGE, ERIS, and MERGE-ETL. Since the databases of most of these models are huge, we restricted our analysis to technology characterisation data that influence costs of three different technologies. These technologies are wind turbines (on shore and off shore), hydro plants (varying from pumped storage hydro in one model to small run-of-the-river hydro power plants in another) and grid-connected PV-systems.

The time span of the different models varies substantially. POLES, PRIMES, MERGE-ETL and ERIS provided data up to 2030. MARKAL (i.e. the database for SAPIENT) includes data up to 2050. MESSAGE data continue until 2100. Another difference between the models is that ERIS and MERGE-ETL are purely ETL models. This means that these models only include investment cost data for the first model year exogenously. The investment costs for the other years are calculated within the model. These outcome data are not presented here. They would obviously differ per scenario. Therefore the input data for the ETL models ERIS and MERGE-ETL are presented as being constant over time. The other models can also run in the ETL-mode, but are still often used as non-ETL models. So, for POLES, PRIMES, MESSAGE and MARKAL the input data from the non-ETL variants have been used to compare the data that are the result of different expert opinions on future cost trends.

The data from MARKAL are the data used in the Western Europe (i.e. EU plus Norway and Switzerland) database of this model. MESSAGE data represent estimated global averages. PRIMES cover data on all the EU Member States. POLES, ERIS and MERGE-ETL are global models with regions (EU is one of these).

Data on renewable technologies in PRIMES recently have undergone a large revision. Data have been differentiated per EU Member State. In the comparison the simple average of these data has been used as a proxy for the PRIMES-data.

All data have been converted into US$ of the year 2000. This has been done in the case of non-US currencies (ECU, Euro) of other years by first converting into US$ in that year and then converting to US$ of the year 2000, using the US Consumer Price Index.

## D.3 Comparison of model data

### D.3.1 Investment costs

*Hydropower*
Table D.1 gives an overview of the different investment costs assumptions in the different models with regard to hydropower options:

Table D.1 *Overview of investment costs for hydropower technologies in the different models [US$(2000)/kW]*

| | | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 | 2060 | 2070 | 2080 | 2090 | 2100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MESSAGE | high | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 | 4018 |
| | low | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 | 1339 |
| MARKAL | medium and high head | 2328 | 2346 | 2362 | 2380 | 2397 | 2415 | 2431 | | | | | |
| | low head | 3696 | 3696 | 3696 | 3696 | 3696 | 3696 | 3696 | | | | | |
| | pumped storage | 3403 | 3403 | 3403 | 3403 | 3403 | 3403 | 3403 | | | | | |
| ERIS | | 3562 | 3562 | 3562 | 3563 | 3562 | 3562 | 3562 | | | | | |
| POLES | | 4580 | 4336 | 4123 | 3876 | 3665 | | | | | | | |
| PRIMES(Run of river) | small | | 2055 | 1958 | | 1860 | | | | | | | |
| | medium | | 2209 | 2104 | | 1999 | | | | | | | |
| | large | | 2362 | 2250 | | 2137 | | | | | | | |

Figure D.1 gives the same figures, but now presented graphically.

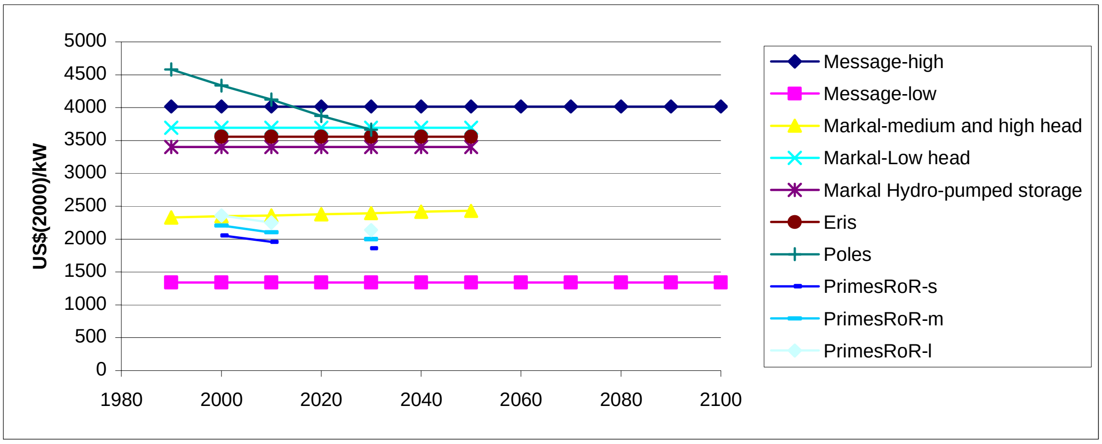


Figure D.1 *Overview of investment costs for hydro power technologies in the different models*

Analysing the table and figure several specific observations with regard to investment costs for hydropower can be made:

- The estimation of investment costs for hydropower technologies range from less than 1500 $/kW to over 4000$/kW.
- These differences are partly due to different circumstances in which hydropower stations can be building. Most of the models make this explicit by defining a set of different hydro technologies: high head or low head (MARKAL), high costs or low costs (MESSAGE) or small, medium and large Run of the River-systems (PRIMES).
- POLES and Eris only have one hydro technology defined. Both these models have estimations that are on the high side of the range. Apparently these models refer to low-head, small-scale hydro technologies only.
- The POLES and the PRIMES model are the only models that assume that cost reductions for hydro technologies will be realised in the future. The other models assume constant investment costs for hydro technologies, apparently considering hydro as a technology with no learning potential anymore.
- In the case of medium and high-head hydropower the MARKAL model assumes a slight increase of costs (this might reflect the expectation that stricter environmental rules will apply to large-scale hydropower stations in the future which will lead to some extra required investments). This is a similar trend to what has happened in the nuclear sector.
- Since Run-of-River systems often are low-head options, these figures from PRIMES can be best compared to the low-head or large-scale options in the other models. This shows that the PRIMES figures are substantially lower than the figures in the other models.

*Wind power*

Table D.2 gives an overview of the different investment costs assumptions in the different models with regard to wind power options:

Table D.2 *Overview of investment costs for wind power technologies in the different models [US$(2000)/kW]*

| | | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 | 2060 | 2070 | 2080 | 2090 | 2100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MESSAGE | | 1875 | 1748 | 1458 | 1153 | 864 | 648 | 589 | 536 | 496 | 450 | 423 | 387 |
| MARKAL | inland | 1566 | 1361 | 1178 | 1144 | 1144 | 1144 | 1144 | | | | | |
| | coast | 1538 | 1341 | 1144 | 1116 | 1116 | 1116 | 1116 | | | | | |
| | near-shore | | 2627 | 2056 | 1824 | 1715 | 1661 | 1634 | | | | | |
| | offshore | | | 2464 | 2178 | 2056 | 1988 | 1960 | | | | | |
| Eris | | | 1035 | 1035 | 1035 | 1035 | 1035 | 1035 | | | | | |
| POLES | | | 2021 | 1940 | 1860 | 1779 | | | | | | | |
| Merge-ETL | | | 986 | 986 | 986 | 389 | 389 | 389 | | | | | |
| PRIMES Onshore | small | | 999 | 833 | | 666 | | | | | | | |
| | medium | | 959 | 799 | | 639 | | | | | | | |
| | large | | 979 | 816 | | 653 | | | | | | | |
| Offshore | small | | 2107 | 1756 | | 1405 | | | | | | | |
| | medium | | 1985 | 1654 | | 1323 | | | | | | | |
| | large | | 2038 | 1698 | | 1358 | | | | | | | |

Figure D.2 gives the same figures, but now presented graphically.

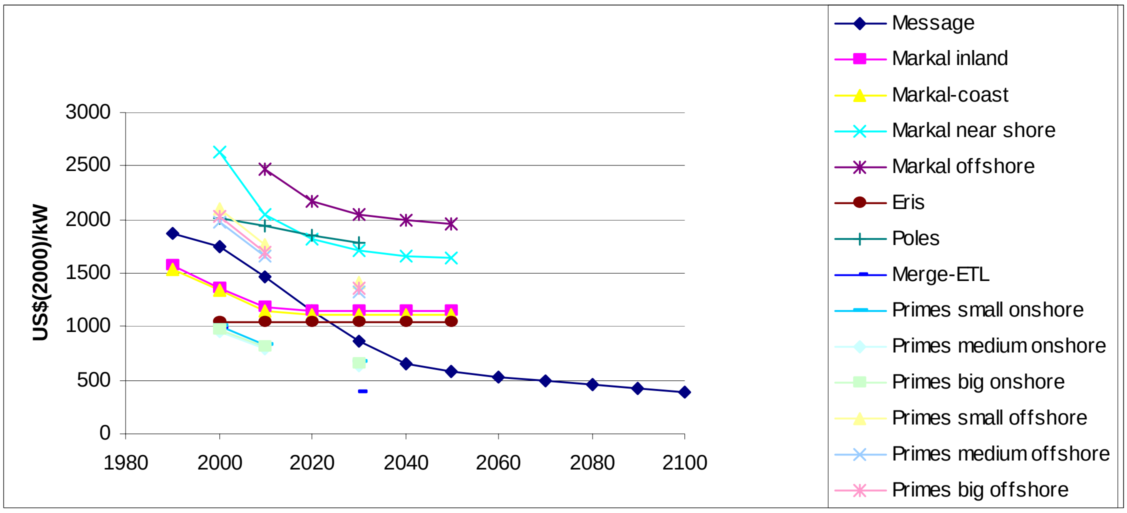


Figure D.2 *Overview of investment costs for wind power technologies in the different models*

Analysing the table and figure several specific observations with regard to investment costs for wind power can be made:

- There are large differences between the estimated costs for wind power. Onshore wind power investment costs for the year 2000 for instance vary from 959 $/kW (PRIMES-medium) to 1748 $/kW (MESSAGE) and even 2021 $/kW (POLES). However most models assume investments costs of around 1000 $/kW in 2000.
- The POLES figures for wind power investment costs correspond to the estimated costs of wind offshore technologies in the other models. These cost estimations for the year 2000 range from 1985 $/kW (PRIMES-medium) to 2627 $/kW (MARKAL near-shore). This is still a difference of more than 30%.
- All models assume that investment costs for wind will decline in the future. MARKAL assumes this learning effect will stop after 2020. Other models assume continuous cost reductions, until a level of around 400 $/kW for onshore wind (in 2100).
- The differences between the different options for PRIMES (small, medium and large) are not substantial. It seems as if the model could be simplified by only defining one on-shore and one offshore technology.

*Solar PV*

Table D.3 gives an overview of the different investment costs assumptions in the different models with regard to solar PV.

Table D.3 *Overview of investment costs for solar PV technologies in the different models [US$(2000)/kW]*

| | | 1990 | 2000 | 2010 | 2020 | 2030 | 2040 | 2050 | 2060 | 2070 | 2080 | 2090 | 2100 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MESSAGE | | 6830 | 6190 | 4780 | 3419 | 2158 | 1157 | 970 | 813 | 695 | 581 | 505 | 426 |
| MARKAL | North-Eur. | | 6807 | 2695 | 2076 | 1457 | 1266 | 1266 | | | | | |
| | South-Eur. | | 6807 | 2695 | 2076 | 1457 | 1266 | 1266 | | | | | |
| | Central Eur. | | 6807 | 2695 | 2076 | 1457 | 1266 | 1266 | | | | | |
| | Import from Africa | | 7828 | 3744 | 2695 | 2076 | 1457 | 1457 | | | | | |
| Eris | | | 5000 | 5000 | 5000 | 5000 | 5000 | 5000 | | | | | |
| POLES | Rural in DC | | 22896 | 21409 | | 18436 | | | | | | | |
| | Roof with grid | | 13016 | 7999 | 7228 | 6457 | | | | | | | |
| PRIMES | small | | 4500 | 2850 | | 1150 | | | | | | | |
| | medium | | 4500 | 2850 | | 1150 | | | | | | | |
| | large | | 4500 | 2850 | | 1150 | | | | | | | |

Figure D.3 gives the same figures, but now presented graphically.

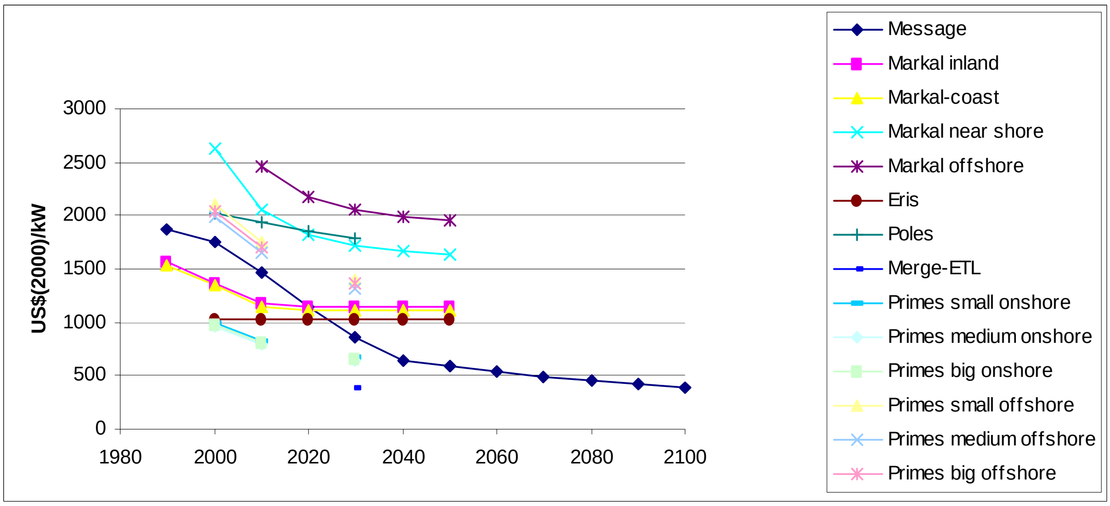


Figure D.3 *Overview of investment costs for solar PV technologies in the different models*

Analysing the table and figure several specific observations with regard to investment costs for solar PV technologies can be made:

- Most models converge with regard to investment costs estimations for the year 2000 around 5000 $/kW. PRIMES has an estimate just below that, MESSAGE and MARKAL just above this level.
- POLES figures are substantially higher than those of the other models. One technology option in POLES (PV for rural areas in developing countries) can be regarded as another tech-

nology (solar home systems). For the other POLES options the reasons of this difference is not clear.
- MARKAL, POLES and PRIMES assume a very substantial cost reduction in the first decade of the 21st century. After that the speed of cost reductions slow down in this model.
- Expected prices in 2030 for models other than POLES vary between 1150 \$/kW (PRIMES) and 2158 \$/kW (MESSAGE). MESSAGE estimates for 2040 are close to the 1200 \$/kW figures of the other models.
- MESSAGE expects continuing declining costs at least until the year 2100 (426 \$/kW).

*General conclusions with regard to investment costs*

A detailed analysis of the investment costs of just three technologies shows that large differences (up to 100%) in investment cost estimations exist between the different models. Sometimes this can be explained by differences in assumptions about a certain variant of the technology (e.g. high-head or low-head hydropower, wind onshore or wind offshore). However, this is not always the case. Since investment costs are one of the major determinants of electricity production costs in the case of renewable technologies, these differences in assumptions lead without any doubt to differences in model outcomes.

### D.3.2 Fixed Operation and Maintenance (O&M) costs

The next three figures give a summary of O&M costs estimates for the same three renewable technologies in the different models:

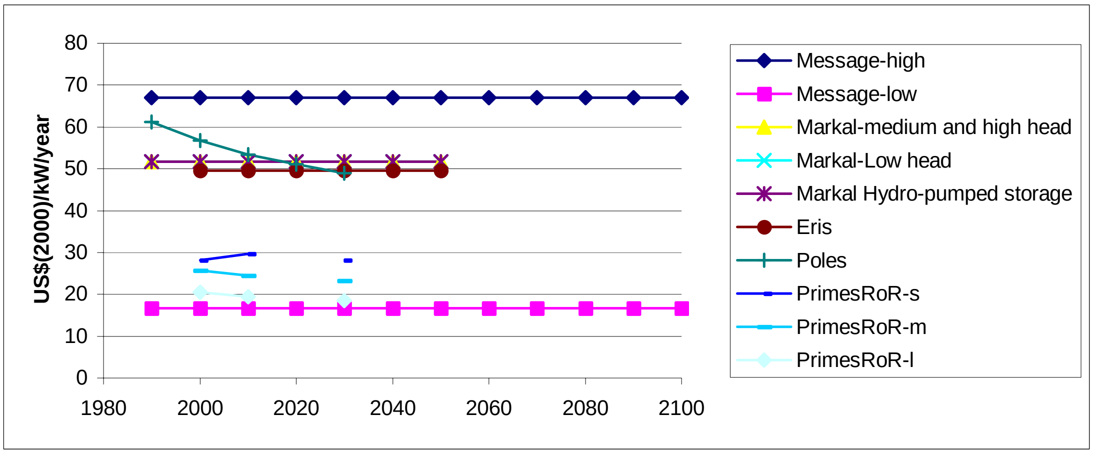


Figure D.4 *Overview of fixed O&M costs for hydropower technologies in the different models*

Looking at Figure D.4 the following observations can be made:
- All estimates are between the MESSAGE-high and MESSAGE-low estimates.
- Except for POLES none of the models assume cost reductions for fixed O&M costs for hydropower.
- MARKAL, POLES and Eris assume fixed O&M costs for hydro of about 50 \$/kW/year
- PRIMES figures are about 50% lower than the estimates of MARKAL, POLES and Eris

Fixed O&M costs for hydro contribute to about 10% of the hydro electricity production costs. A difference of 50% in fixed O&M costs leads to a difference of about 5% in calculated production costs. Clearly the importance of fixed O&M costs is not as important as investment costs assumptions in the case of hydro technologies.

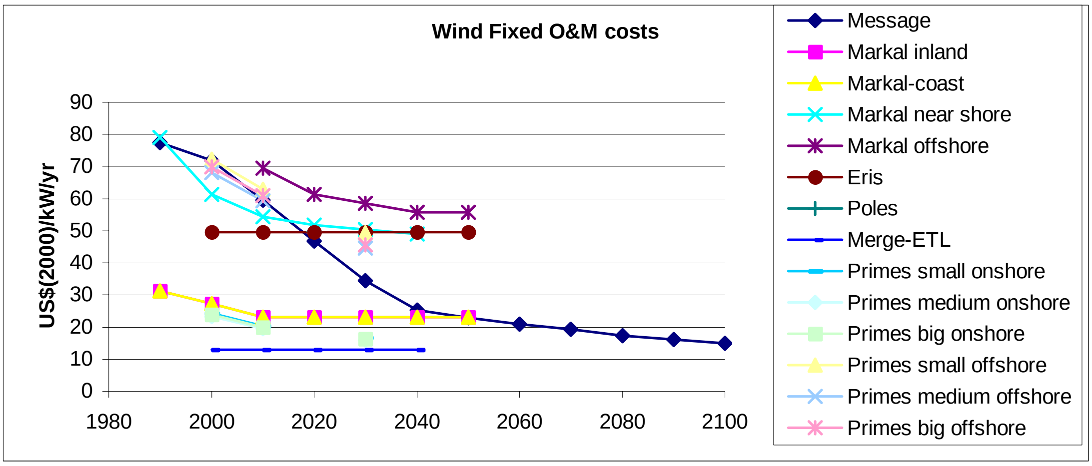


Figure D.5 *Overview of fixed O&M costs for wind power technologies in the different models*

Looking at Figure D.5 the following observations can be made:

- All models assume future costs reductions for fixed O&M costs in the case of wind energy, except for Eris and Merge-ETL.
- MESSAGE is rather pessimistic compared to the other models. Current cost levels will only be reached at the end of the 21$^{st}$ century in the MESSAGE model.
- Eris is also rather pessimistic compared to the other models.
- PRIMES, MARKAL and POLES' estimations for fixed O&M costs for wind come pretty close to each other:
  - They all assume current fixed O&M costs for wind offshore options of about 60-70 $/kW/year. Over time this will be reduced to about 50 $/kW/year.
  - They all assume current fixed O&M costs for wind onshore options of about 30 $/kW/year, which will be reduced to 15-20 $/kW/year in the future.

Fixed O&M costs contribute to about 15-20% to electricity production costs in the case of wind energy. With the small differences in input costs data for PRIMES, MARKAL and POLES, will not have a big impact on model outcomes. The difference with the models Eris and especially MESSAGE however might lead to a difference in outcome of about 5-10%.

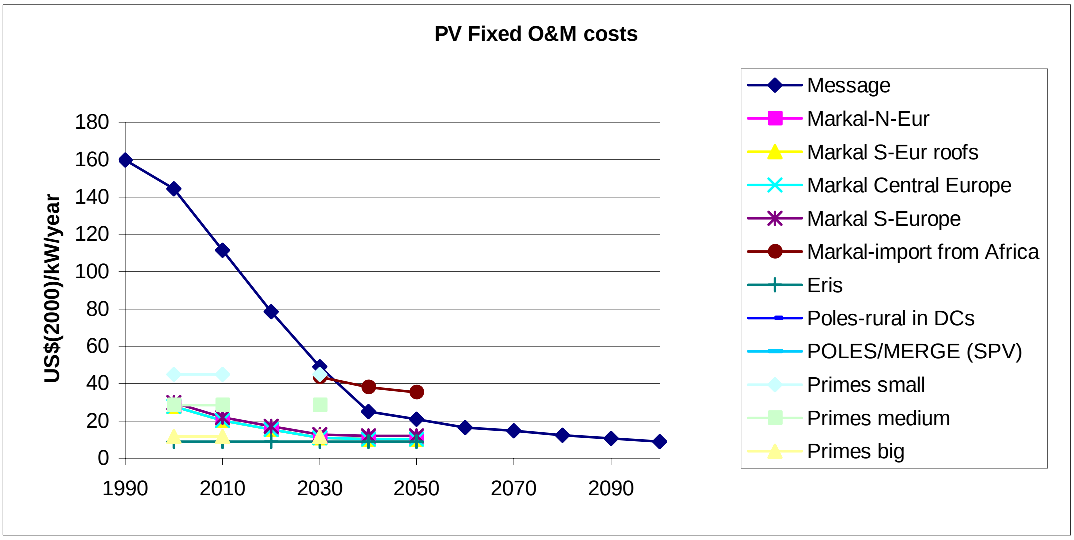


Figure D.6 *Overview of fixed O&M costs for solar PV technologies in the different models*

Looking at Figure D.6 the following observations can be made:

- Also for solar PV, MESSAGE has by far the highest fixed O&M costs assumptions (more than 140$/kW/year in the year 2000).
- The differences in the other models are also quite substantial. From 10 $/kW/year to about 45 $/kW/year. For PRIMES this is related to the size of the units. Smaller units have higher fixed O&M costs than larger units.
- PRIMES and Eris do not assume any cost reductions over time.

With fixed O&M costs of about 30 $/kW/year the contribution to electricity production costs is somewhere between 5% and 10%. Except for the MESSAGE figures, this means that the differences in outcomes for electricity production costs will not be substantial.

*Fixed O&M costs conclusions*

In the case of hydropower substantial differences exists between the estimation of fixed O&M costs. For wind and solar technology these differences are lower, at least for most models. Since for renewable energy technologies fixed O&M costs do not constitute a substantial part of electricity production costs, these differences are not that important. However, added up to other differences (in investment costs or other cost-influencing variables), it contributes to differences in outcomes. Another important observation is that, whereas investment costs are often assumed to decline over time, this is not always the case for fixed O&M costs. Whether this is due to expert opinions that do not expect any decline in these costs over time, or whether it is due to a lack of study and understanding of O&M-cost processes and developments within these processes, is something to be made clearer in the future.

### D.3.3 Variable Operation and Maintenance (O&M) costs

The three figures below give an overview of the differences in variable O&M costs for the three renewable technologies.

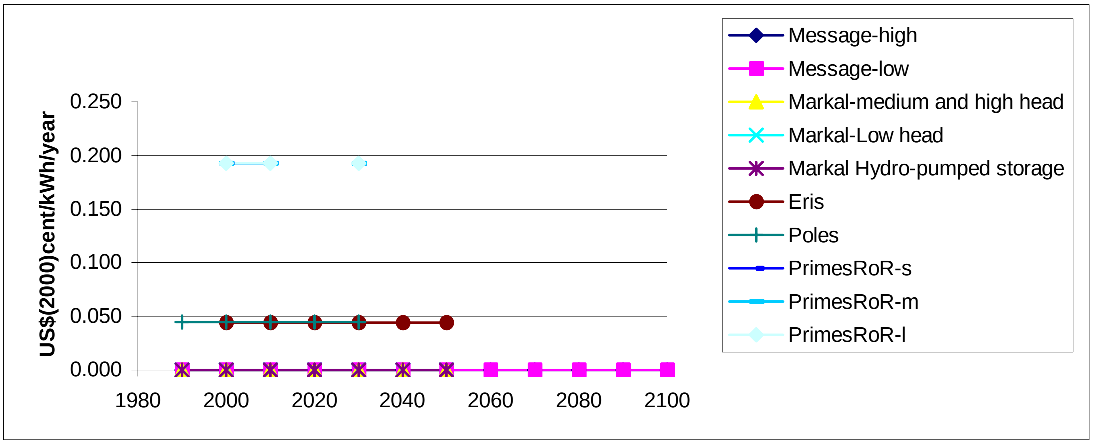


Figure D.7 *Overview of variable O&M costs for hydropower in the different models*

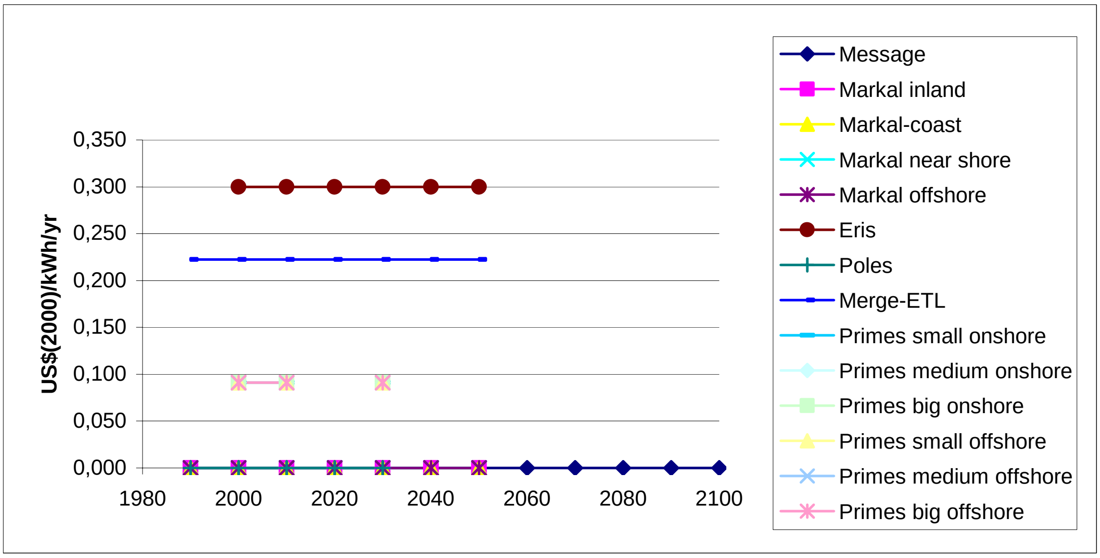


Figure D.8 *Overview of variable O&M costs for wind power in the different models*

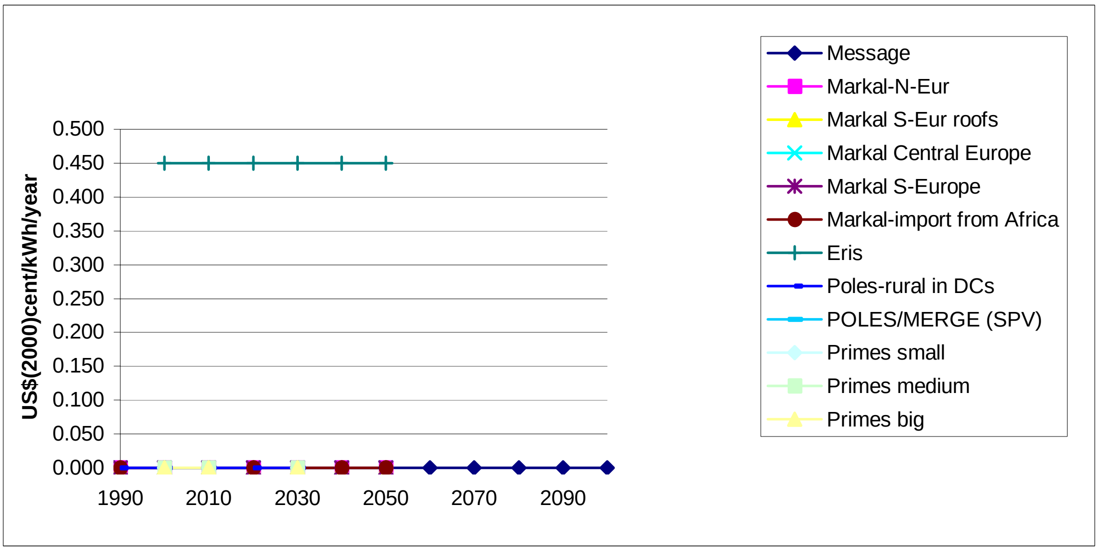


Figure D.9 *Overview of variable O&M costs for solar PV technologies in the different models*

As is apparent in Figures D.7 to D.9 the estimates for variable O&M costs apparently are an under-studied item. There is only one model (POLES) that has estimated any values for variable O&M costs for all three technologies. The others either think there are not always variable O&M-cost or have estimated it to be too unimportant to put any effort in establishing good figures for this. What is striking is that none of the models assumes any variable O&M cost reductions over time. This seems highly unlikely in case of new technologies for which much learning still can be expected (wind and solar). That variable O&M costs are important can be seen when comparing the costs that are assumed (if they are assumed) with electricity market prices: 0.3 $cents/kWh is in the neighbourhood of 10% of electricity market prices, which is not negligible.

### D.3.4 Lifetime

The next three Figures give an overview of another factor that determine electricity production costs in the different models: the lifetime of the technology.

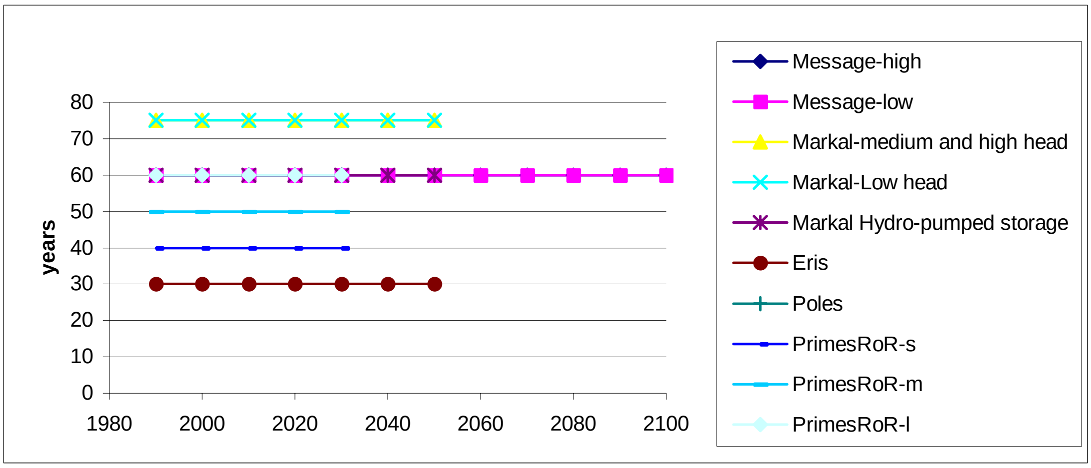


Figure D.10 *Estimates for lifetime of hydropower options in the different models*

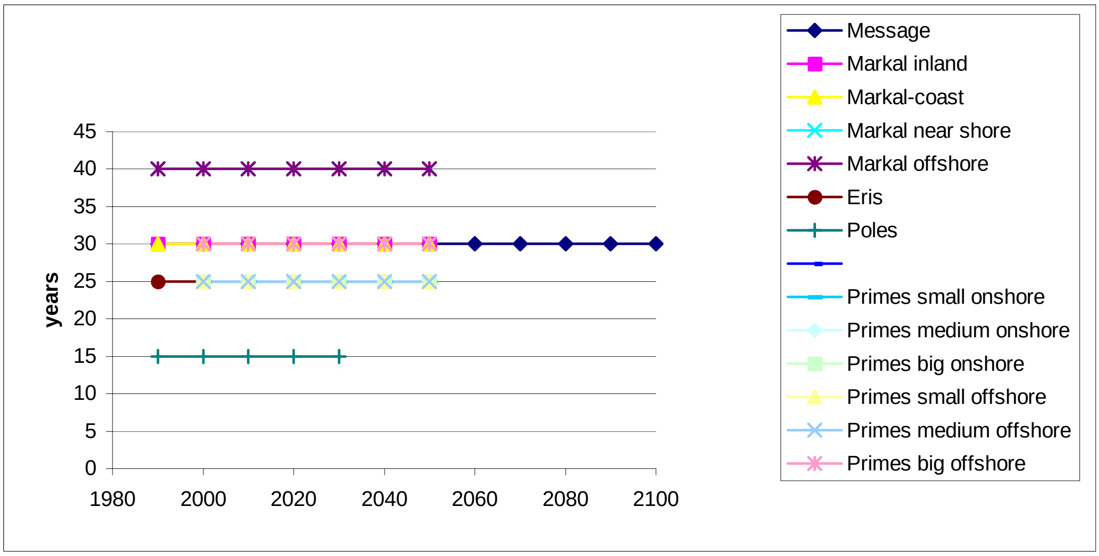


Figure D.11 *Estimates for lifetime of wind power options in the different models*

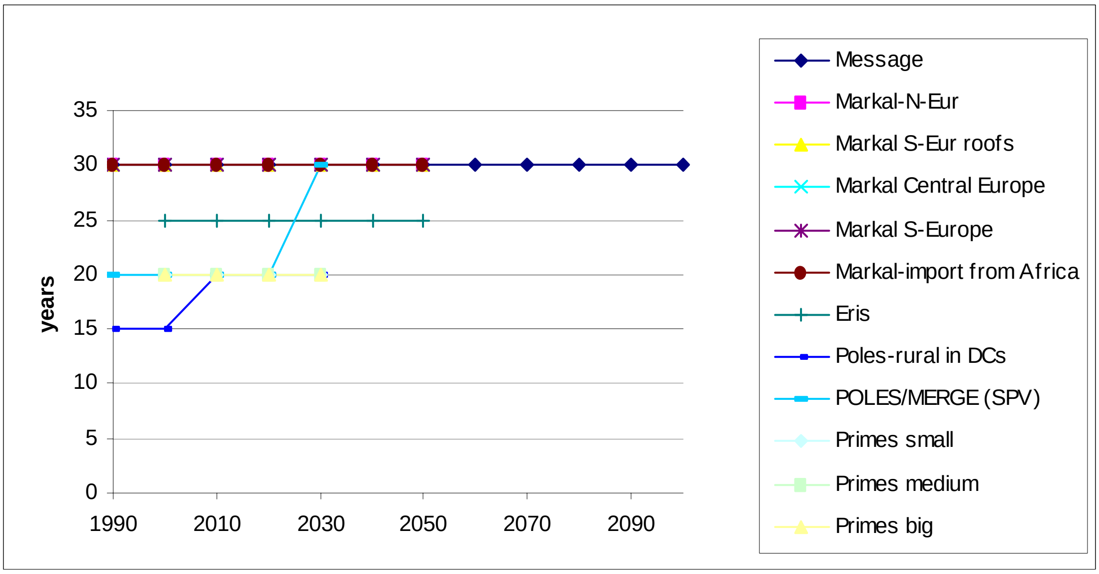


Figure D.12 *Estimates for lifetime of solar PV technologies in the different models*

The following observations can be made:

- For hydro power plants values vary from 30 years lifetime to 75 years lifetime.
- PRIMES data for hydro lifetime vary from 40 to 60 years, depending on the scale.
- For wind lifetime expectations vary also. 30-40 years for wind onshore and 15-30 years for wind offshore.
- For solar PV lifetime expectations vary from 15 to 30 years.
- POLES is the only model that assumes improvements in lifetime figures for one technology: solar PV. In all other cases and in all other models no improvement in lifetime is expected (no learning here).

Lifetime has a substantial impact on electricity production costs. Since differences are large in the models (in the order of 100%), electricity production costs outcomes will also be very different. Longer lifetimes will in general favour capital-intensive technologies such as renewable technologies.

### D.3.5 Availability

A last input data set that cannot be neglected is the number of hours per year a technology is assumed to be able to produce at full capacity: the availability of the technology. The availability of capital-intensive technologies is, apart from variable O&M costs, inversely linear with the electricity production costs. In the next three Figures you will find the input model data on this aspect for the different models.

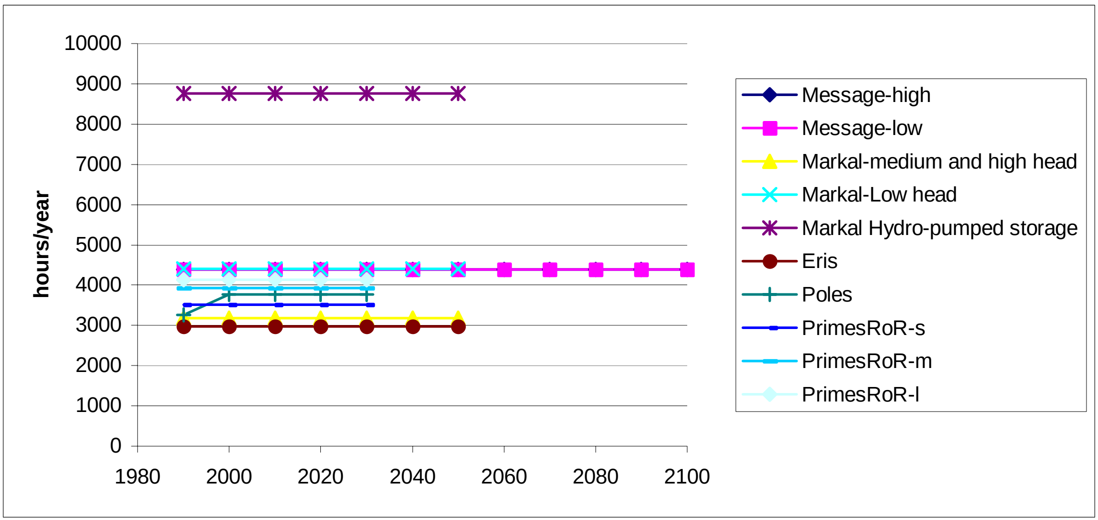


Figure D.13 *Estimates for availability of hydropower options in the different models*

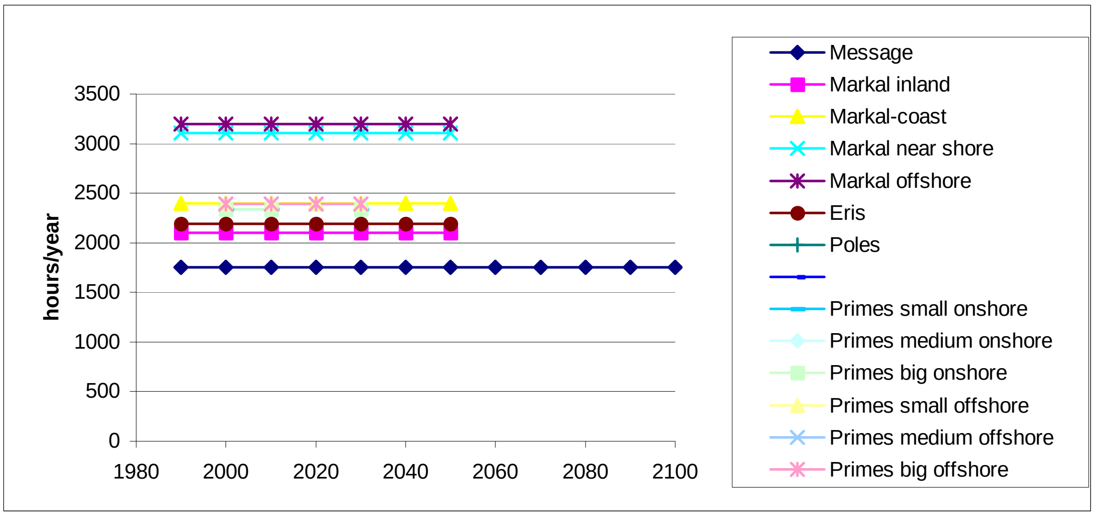


Figure D.14 *Estimates for availability of wind power options in the different models*

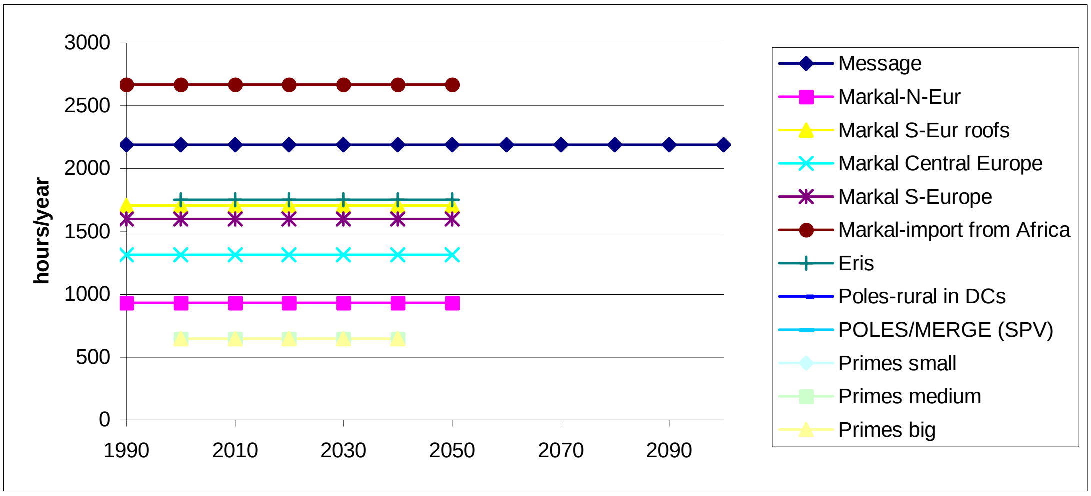


Figure D.15 *Estimates for availability of solar PV technologies in the different models*

The following observations can be made:

- For hydro the ERIS assumptions seem to be on the low side comparing it to the other models. The MARKAL-hydro pump storage figures compares to 100% availability, which might be possible in the case of pumped storage facilities.
- In general hydro figures for availability varies from 3500 to 4500 hours/year. This is still a difference of a little bit less than 30%.
- For wind offshore the figures vary from 2400 hours/year (PRIMES) to 3200 hours/year (MARKAL). This is a difference of 33%.
- For wind onshore the figures vary from 1600 hours/year to 2200 hours/year. This is a relative difference of 35%-40%.
- The PV availability varies very much with a reason. It is the way to distinguish PV-technology applications in different areas of the world. Still the MESSAGE figure of 2200 hours as a world average seems very high, whereas the PRIMES average of 600 hours for Europe might be on the low side. Compared to MARKAL northern Europe figures (900 hours) this is a relative difference of 30%.
- In none of the models for none of the technologies availability is expected to increase. Apparently the modellers estimate that no efficiency gains can be expected anymore with regard to the current state-of-the-art in hydro, wind and solar power technology.

In general one can observe that availability figures differ substantially from each other, whereas availability is one of the most important factors in calculating electricity production costs.

## D.4 Conclusions and recommendations

The following conclusions can be drawn:

- Most attention and efforts have been spent to investigating the development of investment costs. There is a lack of knowledge on the development of the other 4 factors that determine electricity production costs: Fixed O&M costs, variable O&M costs, lifetime and availability.
- Recent insights in developments in investment costs (Technology Improvement Database) have not always been implemented in the models. Investment costs figures have only be used to estimate learning curve factors, not to harmonise year 2000 investment costs assumptions.
- There is a need for a better investigation of the other factors influencing electricity production costs.
- Especially (developments in) availability and lifetime deserve attention and harmonisation.
- Although O&M costs are somewhat less important for capital-intensive technologies such as renewable, differences can still be substantial. More knowledge and discussion is needed on these items.
- In general it can be concluded that more time and attention for model data in future work will enhance the quality of models and the comparability of their outcomes.

# LIST OF ABBREVIATIONS

| | |
|---|---|
| DG RES | Directorate-General for Research |
| ECN | Energy research Centre of the Netherlands |
| ERIS | Energy systems model developed within TEEM project |
| EU | European Union |
| ETL | Endogenous Technological Learning |
| ISPA | Integrating System for Priority Assessment |
| MARKAL | Market Allocation |
| MCA | Monte Carlo Analysis |
| MESSAGE | Energy systems model of IIASA |
| MIP | Mixed-Integer Programming |
| NLP | Non-Linear Programming |
| POLES | Global energy simulation model |
| PR | Progress Ratio |
| PV | Photovoltaic |
| RD&D | Research, Development & Demonstration |
| SAPIENT | Systems Analysis for Progress and Innovation in Energy Technologies, EU research project |
| TEEM | Energy Technology Dynamics and Advanced Energy System Modelling, EU research project |
| 1FLC | One Factor Learning Curve |
| 2FLC | Two Factor Learning Curve |