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Technological Learning in Energy Models: Experience and Scenario Analysis with MARKAL and the ERIS Model Prototype

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Executive Summary

With technology being a fundamental driving factor of the evolution of energy systems, it is essential to study the basic mechanisms of technological change and its role in achieving more efficient, productive and clean energy systems. Understanding its dynamics constitutes a guide for policy formulation and decision making and the conception of effective intervening instruments.

Technology development does not occur as an autonomous independent process, but evolves from a number of endogenous interactions within the social system. Technologies evolve and improve only if experience with them is possible. Cumulative learning, both in R&D activities and the marketplace is, in fact, one of the basic mechanisms in the emergence and replacement of technological regimes.

Thus, efforts must be devoted to improve our analytical tools and decision-support frameworks concerning the treatment given to the technological variable. Despite its undeniable importance, several technological factors have been traditionally addressed in an oversimplified way in energy optimisation models, without recognising the cumulative and gradual nature of technological change and the important role that learning processes play in achieving performance increases in a given technology or group of them.

This report presents a collection of works developed by the authors concerning the endogenisation of technological change in energy optimisation models, as a contribution to the Energy Technology Dynamics and Advanced Energy System Modelling Project (TEEM), developed in the framework of the Non Nuclear Energy Programme JOULE III of the European Union (DGXII). Here, learning curves, an empirically observed manifestation of the cumulative technological learning processes, are endogenised in two energy optimisation models. MARKAL, a widely used bottom-up model developed by the ETSAP programme of the IEA and ERIS, a model prototype, developed within the TEEM project for assessing different concepts and approaches. The incorporation of the curves provides the model with a mechanism to represent path-dependence and self-reinforcing phenomena intervening in shaping the technological trajectories of the system.

The methodological approach is described and some results and insights derived from the model analyses are presented. The incorporation of learning curves results in significantly different model outcomes than those obtained with traditional approaches. New, innovative technologies, hardly considered by the standard models, are introduced to the solution when endogenous learning is present. Up-front investments in initially expensive, but promising, technologies allow the necessary accumulation of experience to render them cost-effective. When uncertainty in emission reduction commitments is considered, the results point also in the direction of undertaking early action as a preparation for future contingencies. Early investments stimulating technological learning prove beneficial in terms of both lower costs and emissions in the long run. On the other hand, when the learning rates of the technologies are uncertain, a more prudent intermediate path of

installations is followed, but technological learning in emerging technologies continues to be an important hedging mechanism to prepare for future actions. Increasing returns associated to the effects of learning and uncertainty emerge as core mechanisms of the technological change process.

The results obtained using this modelling approach provide some important policy insights. Early investments on sustainable technologies, both in R&D, demonstration projects and niche markets, are required in order to ensure that they move along their learning curves and achieve long run competitiveness. New technologies will become competitive only if cumulative experience and investments are made. Their successful introduction requires then the promotion of innovation and learning at multiple technological, social and institutional levels.

It is necessary to advance further in the endogenisation of technological change into energy planning models. The treatment given to technology dynamics affects our understanding of a number of issues concerning the future structure of global energy systems and their environmental impacts (e.g. contribution to climate change). An adequate framework is necessary for gaining insights about the underlying forces that drive this evolution.

Therefore, other aspects of technological change, related, for instance, to other intervening factors such as R&D expenditures, or the spatial and temporal patterns of technological diffusion must be incorporated. It is also important to examine the interrelations between uncertain technological learning and policies for greenhouse gases reduction, examining the mutual impacts both on the technological evolution and the costs of abatement strategies and to address aspects such as "spill-over" of learning and co-evolution of technologies in clusters. In addition, different procedures to handle uncertainty in the learning processes and other technical and economic variables should be explored. Also, a careful technology characterisation and the study of the main driving factors of technological change must support the assumptions for the learning process and complement the analysis.

1. Introduction

Technology constitutes one of the main driving forces of economic growth (Cameron, 1996). The dynamics generated by the introduction and diffusion of new technologies into the marketplace and the improvement or decadence of the existing ones, determine technological trajectories that become significant conditioning factors on the achievement of sustainable economic, environmental and social goals, both at local and global levels.

Regarding the evolution of the global energy systems, technology plays a fundamental role in determining their cost structure, environmental impacts, flexibility and available policy alternatives (Rogner, 1996a). Technological trajectories condition to a large extent the resulting environmental impacts of the energy resources extraction, transformation, transportation and final use. As the concern to drive energy systems to a sustainable future path grows, technology is bound to play a very important role in the achievement of efficient and clean energy production and consumption. In fact, a transition to an environmentally compatible global energy system will very likely require a transition to a different technological regime (Kemp, 1997a). Hence, the mechanisms and driving forces of the technology evolution, as well as characteristics and structure of prevailing and emerging regimes must be understood in order to conceive the necessary actions to stimulate the change in the required direction. Technological change heading to the de-carbonisation of energy systems, for instance, will only occur if supported by previous research, development, demonstration and diffusion of new technologies (IIASA-WEC, 1998). The successful introduction of new environmentally sound technologies into the marketplace will depend, among other factors, of the cost-competitiveness to the existing ones.

As a complex and not fully understood process, produced by the interaction of many elements, a technological path is not easily predictable. However, even with the difficulties in its foreseeability, a comprehensive framework for its treatment is required (Piater, 1991). The assessment of opportunities for new technologies in shaping future energy systems is a complex task involving the interaction of a number of technical, economic, environmental and social driving forces, but the understanding of the complex dynamics of technology is a central issue in policy decisions concerning the definition of future sustainable trajectories for the energy systems (Kemp, 1997a).

Technology has a dynamic, always evolving, nature (Grübler, 1998), and learning processes play a very important role in this constantly changing technological environment. Learning is a cumulative, gradual process, which manifests itself at all levels of a society (Marchetti, 1980). Learning allows to improve performance and productivity as knowledge cumulates and experience is gained through a number of sources. Technological learning has been empirically observed in many fields (Argote and Epple, 1980) and is customarily represented using the so-called learning, or experience, curves. Several examples of them have been provided in the literature (Ayres and Martinàs, 1992, Christiansson, 1995).

Energy systems models are employed as a supporting tool to develop energy strategies, outlining the likely future structure of a given system and as such, they provide insights on the technological paths, structural evolution and policies that should be followed (Mattson and Wene, 1997). The manner in which the technological dynamics is considered in these models has a significant influence on the results and consequent policy decisions. There is a recognised necessity for better treatment of technological dynamics in the energy decision frameworks.

In fact, an interesting point about the learning curves is that they express the fact that experience is required if a technological process is going to improve and become competitive. That is, technologies will not evolve unless experience with them is possible. This basic fact actually contradicts the traditional approach to handle technology within the energy analysis models. A series of factors reflecting the dynamics of technological change, such as the cost and efficiency evolution of technologies, the market penetration mechanisms, the influence of R&D expenditures, the inertia and capacity of change of the system, among others, have been traditionally handled in an exogenous manner or not considered at all in the traditional modelling approaches examining future perspectives of the energy systems. Technological development, however, is not an autonomous but an endogenous process, where both R&D and the market intervene and influence each other (Grubb, 1997).

In linear programming models, extensively used for energy modelling purposes, technological change is customarily introduced as an exogenous parameter. The cost and technical parameters for a given technology are considered either constant (static model) or as an exogenous function of time (dynamic model). These two approaches have been criticised. When considering investments costs, for instance, the static approach considers no improvements in the technology costs. In the dynamic one, the model makes use of a given technology once its costs have declined, and thus, it is not able to reflect the earlier investments, necessary to promote its successful introduction. This is the so-called "manna from heaven" approach to consider technological innovation. Costs reductions are assumed to occur at no additional cost. This approach does not recognise the need for accumulating the necessary knowledge base in order for the technology to achieve competitiveness (Messner, 1997).

A better representation may be obtained when technological change is endogenised. The incorporation of learning curves provides a more consistent model behaviour regarding the penetration of technologies into the system. The model outcomes differ substantially from those of the traditional exogenous specification of technology dynamics. When technology dynamics is endogenous, the early investments required for new technologies to achieve long-run competitiveness in the marketplace are reflected.

This report collects several works carried out the authors, concerning the endogenous incorporation of technological learning in energy optimisation models. This work has been performed within the framework of the TEEM Project, developed by an international group of partners[1] for the European Commission. TEEM has devoted efforts to "analyse energy technologies and accompanying policy in the European Union by using advanced energy technology models emphasising on technology evolution dynamics" (TEEM, 1997) [2].

The endogenisation of learning curves has been performed here in two main linear programming models. The first one is MARKAL (MARKet ALlocation), a bottom-up technology oriented model, developed by the Energy Technology Systems Analysis Programme (ETSAP) of the International Energy Agency (IEA) and extensively used in a number of countries for national and international studies (Fishbone and Abilock, 1981). The second is the ERIS (Energy Research and Investment Strategy) model prototype developed as a joint effort by several partners within the TEEM Project. The methodology is described and some applications using these two mentioned models are presented.

The structure of this document is as follows. Section 2 presents a brief description of the learning curve and some associated concepts. Section 3 describes the mathematical approach for endogenising the curves in the optimisation models. Section 4 presents some illustrative results for a simplified representation of the global electricity generation system using both models. The structural differences between non-learning and learning models are highlighted and the influence of some parameters in the methodology are analysed with ERIS. Sensitivities to the progress ratio values and the discount rate and the effect of two-stage learning are illustrated with MARKAL. In section 5, an analysis of impacts of Kyoto-like CO_2 emission constraints in the global electricity generation system using the multi-regional version of ERIS is presented and the effects of uncertainty in emission constraints, demand and learning rates are examined using a two-stage stochastic programming approach. Finally, section 6 presents some methodological conclusions, policy insights and proposals for further work. The MARKAL code is listed in the Appendix.

[1] NTUA, IER, IEPE/CNRS, IPTS, KUL, PSI, ESD, ECN, IIASA

[2] For a synthesis of the experience with endogenous technological change in perfect foresight models within the TEEM project, see Seebregts et al. (1999a)

2. The learning curve

A learning, or experience, curve shows how the experience improves performance in a certain activity (Conley, 1970). Thus, a generic learning curve relates a certain performance index to a quantity measuring cumulated experience (Robinson, 1980). However, the most common specification describes the specific cost of a certain technology as a function of the cumulative capacity, which is used as a proxy for the cumulated knowledge. This curve reflects the fact that some technologies may experience declining costs as a result of its increasing adoption, due to the accumulation of knowledge. Learning has many different sources, such as production (learning-by-doing), usage (learning-by-using), R&D, interaction with other social actors (learning-by-interacting), among others. (Grübler, 1998). There are a number of technical, social, economical, environmental and organisational factors which influence the presence (or absence) and rate of technological learning processes.

Technological learning is associated to increasing returns (to scale and to adoption). The more experience is accumulated with a technology the better its performance/cost ratio will be and the more likely that further adoption of the technology occurs (Isoard,1996). The increasing returns lead to self-reinforcing processes, where positive feedbacks act upon the system, contributing to reinforce a given trajectory (Arthur, 1988). Therefore, the concept of increasing returns is one of the keys to explain phenomena of technological "lock-in"[3], as the underlying mechanism favours the penetration of leading technologies, which for some reason were able to gain a certain advantage, preventing or making difficult the introduction of competing ones (Arthur, 1988).

The customary form to express an experience curve is using an exponential regression (Argotte and Epple, 1990):

$$SC(C) = a * C^{-b} \quad (1)$$

Where:

SC: Specific cost
C: Cumulative capacity[4]
b: Learning index
a: Specific cost of the first unit

---

[3] The technological "lock-in" may be described as an historical technological choice which is very difficult to reverse (Grübler, 1998). As a technology becomes dominant in a certain market sector, it is able to increase its comparative advantage, by means of cost/performance improvements, interrelatedness with complementary technologies and the build up of infrastructure and a network of associated social actors, conforming a whole technological regime which will be difficult to challenge and displace (Kemp, 1997b). Sometimes, the system may be locked into a sub-optimal technology (Arthur, 1988).

[4] Although the cumulative capacity CC^{te}_t is defined explicitly as a variable in the MARKAL implementation, in ERIS, the equivalent product G^{te}_t*$dcap^{te}$ is used instead. The parameter $dcap^{te}$ is the initial cumulative capacity and the variable G^{te}_t is the growth factor relative to $dcap^{te}$. However, here reference will be made to CC^{te}_t for explanatory purposes.

The learning index b defines the speed of learning for the technology and constitutes one of the key assumptions. It can be derived from the progress ratio. The progress ratio (*pr*) is the rate at which the cost declines each time the cumulative production doubles. The relation between the progress ratio and the learning index can be expressed as:

$$pr = 2^{-b} \quad (2)$$

One possible alternative is the use of the learning rate, defined as:

$$lr = 1 - pr \quad (3)$$

The parameter a may be computed using one given point of the curve (usually the starting point SC_0, C_0 is specified) as[5]:

$$a = SC_0 \big/ \left(C_0\right)^{-b} \quad (4)$$

Besides the progress ratio, the curve is very sensitive to the starting point (SC_0, $C_{k,0}$), whose definition may pose difficulties for future technologies or those still in the pre-commercial stage (Rogner,1996b).

As an illustration of the sensitivity of a learning curve to its defining parameters, Figure 1 presents an hypothetical learning curve with different values of the progress ratio (0.81,0.85,0.90) but a common starting point ($SC_{k,0}$=5000 US$/kW, $C_{k,0}$ = 0.5 GW). An additional curve, also presented in this figure, with PR=0.85 but a different starting point ($SC_{k,0}$=5000 US$/kW, $C_{k,0}$ =1.5 GW). shows the influence of these parameters.

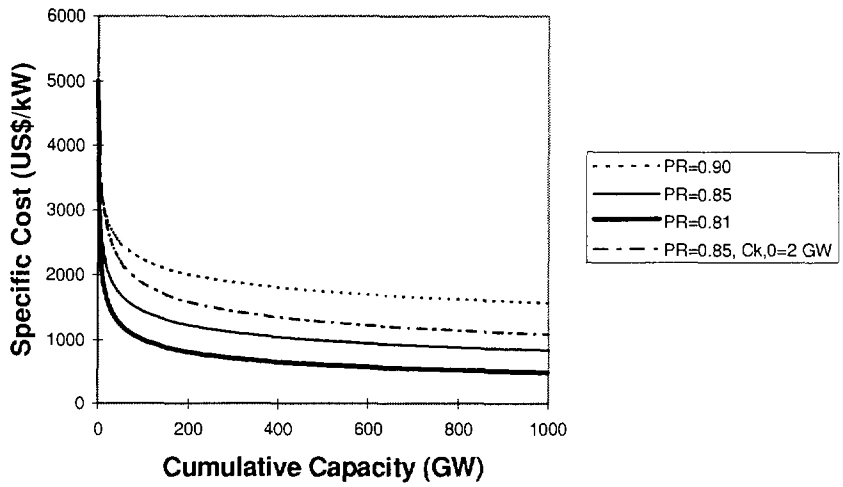

Figure 1. *Learning curves. Different progress ratios*

Evidence of learning processes in many different industries, processes and activities has been collected, and learning curves have been applied to different kinds of analysis. However, although their existence has been well-known for many decades (Wright, 1936), they began to be recognised as a useful planning and management tool in the early 70's

[5] The curve then could also be expressed as: $SC(C) = SC_0 * \left(\dfrac{C}{C_0}\right)^{-b}$

(Conley, 1970, Cunningham, 1980). Figure 2 presents the historically recorded learning curve for solar photo-voltaics in Japan (as presented in Grübler, 1998).

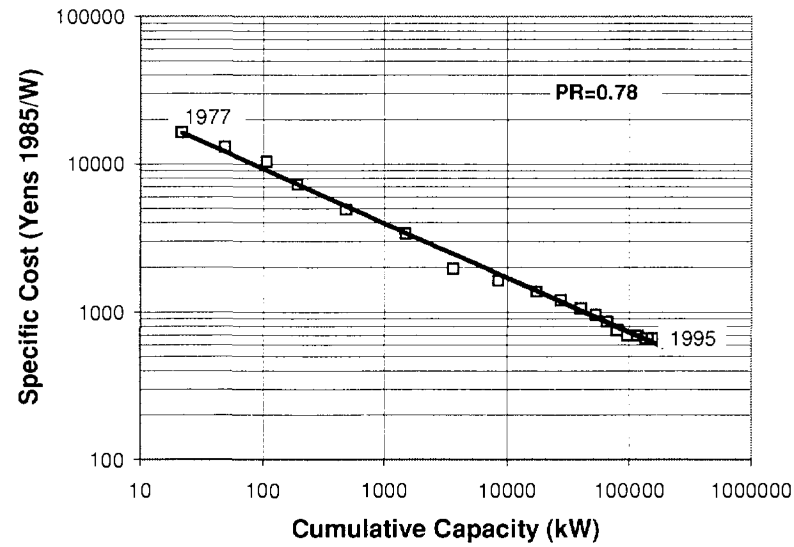

Figure 2. *Learning curve for solar PV in Japan. (Source: Grübler, 1998)*

Efforts have been devoted to establish typical ranges of variation of the progress ratio for different technologies and processes. Argote and Epple (1990) reported learning rates for a number of industries and products. In their sample, the bulk of progress ratios range between 56% and 100%. Christiansson (1995), presented an analysis of learning curves for energy technologies following an stylised taxonomy. This taxonomy considered three main types of plants according to the production processes involved (large plants, modular plants and continuous processes), identifying higher learning potential for the hybrid continuous operation processes, which combine characteristics of both big and modular plants.

In addition, evidence has been gathered pointing to the dependence of the learning process on the technology life cycle (Ayres and Martinàs, 1992, Nakicenovic, 1997). Different stages in the life of a technology may be associated to different speeds of learning. In a R&D intensive phase the technology may experience steeper cost reductions than in the commercialisation phase (Christiansson, 1995). Grübler et al. (1999), for instance, propose a stylised typology of technological development, where the learning rate declines as the technology proceeds from infancy to maturation and ultimately senescence stages.

Although simplified, the establishment of stylised taxonomies of technologies, using the type of production process involved and the life-cycle concept as guides, helps to define plausible ranges for the learning characteristics of new technologies or the possible future behaviour of existing ones (Christiansson, 1995). At this point, it has to be noticed that, when analysing several competing learning technologies, it is not only the absolute form of each learning curve, but their relative ranking what matters (Robinson, 1980).

3. Endogenising learning curves in optimization models

The endogenisation of learning curves in energy optimisation models drives to some mathematical difficulties. The non-linear formulation (NLP) of the learning curves is, due to the presence of the increasing returns mechanism, a non-convex optimisation problem. Such problem possesses several local minima, and a global optimal solution cannot be guaranteed with the normal optimisation solvers. Using Mixed Integer Programming (MIP) techniques, a linearisation of this non-linear, non-convex program, may be achieved. This approach consists of a piece-wise approximation of the total cumulative cost curve where integer variables control the sequence of segments along the curve. Although more computer intensive, it enables to find a global optimum.

Endogenisation of experience curves in energy system models using the MIP approach have been reported by Messner(1997) for MESSAGE and Mattsson(1997) for GENIE. In this section, the NLP and MIP formulations of the learning curves in the ERIS and MARKAL models are described. For the MIP approach two different alternatives are presented. The first one, which corresponds to the one described by Mattsson (1997), was used for the applications reported here. The second one, based on the one presented by Messner (1997), is only briefly described.

The MIP formulation was implemented at PSI for ERIS (Kypreos and Barreto, 1998a) and MARKAL (Kypreos and Barreto, 1998b). Experiences with the MARKAL formulation have been reported for a small scale global electricity system (Kypreos and Barreto, 1998c) and for a large scale European database (Seebregts et al., 1998, Seebregts et al. 1999b).

3.1 Definition of cumulative capacity

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

$$C_{k,t} = C_{k,0} + \sum_{\tau=1}^{t} INV_{k,\tau} \quad (5)$$

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

This is a non-decreasing variable. The parameter $C_{k,0}$ is the initial cumulative capacity (the corresponding cumulative cost $TC_{k,0}$ is also defined). The variable $INV_{k,t}$ represents the investments made on this technology in a particular period t.

3.2 Definition of the cumulative cost curve

The functional form of the learning curve described above is not used directly when the learning curves are endogenised in the optimisation models, because it will lead to a severe non-linearity in the objective function of the problem. The concept of cumulative cost is used instead. The total cumulative cost (*TC*) is expressed as the integral of the specific cost curve (see Figure 3):

$$TC = \int_0^C aC^{-b} * dC = \frac{a}{1-b} C^{1-b} \quad (6)$$

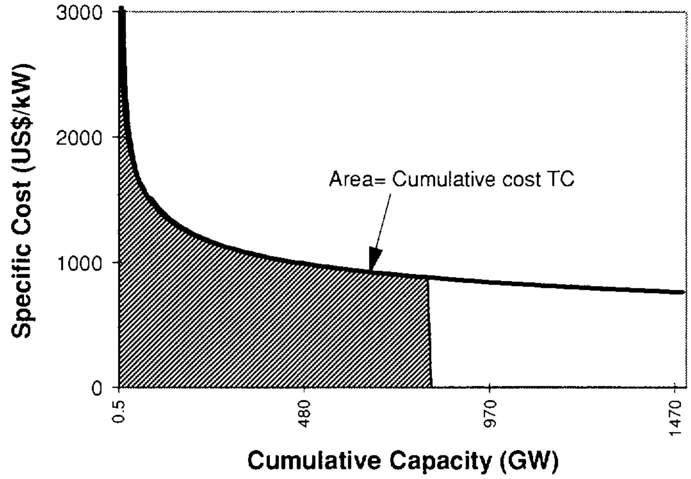

Figure 3. *Cumulative cost curve as the area below the learning curve*

3.3 Definition of the investment cost

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

$$IC_{k,t} = TC_{k,t} - TC_{k,t-1} \quad (7)$$

The discounted investment costs are included in the objective function.

The NLP formulation replaces the equation (6) presented above directly in equation (7) to compute the investment costs per period for a given technology. That is:

$$IC_{k,t} = \frac{a\left(C^{1-b}{}_{k,t} - C^{1-b}{}_{k,t-1}\right)}{1-b} \quad (8)$$

The MIP procedure, on the other hand, provides a piece-wise representation of cumulative cost curve (the curve is approximated by a set of contiguous straight lines, see Figure 4 below) and uses it to compute the corresponding $IC_{k,t}$ term.

3.4 Maximum cumulative capacity and cumulative cost

In order to specify the curve to be interpolated, a maximum cumulative capacity $C_{k,max}$ is defined. $C_{k,max}$ implies an upper bound for the capacity of the technology and will affect the segmentation as discussed below in numeral 4.2.3.3. The corresponding maximum cumulative cost is given by:

$$TC_{k,\max} = \frac{a}{1-b}\left(C_{k,\max}\right)^{1-b} \quad (9)$$

3.5 Declaration of number of segments

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

3.6 Definition of the kink points for cumulative costs and capacities

Using the initial and final points of the curve and according to the number of segments previously defined, the breakpoints are computed. In this particular formulation a segmentation procedure with variable length segments, shorter ones at the beginning and then increasingly longer segments, is used, in order to obtain a better representation for the first region of the curve. The segments are defined as follows:

For i=0,...N-1

$$TC_{i,k} = TC_{0,k} + \frac{\frac{1}{2^{N-i}}\left(TC_{k,\max} - TC_{0,k}\right)}{\sum_{i=0}^{N-1}\frac{1}{2^{N-i}}} \quad (10)$$

And the corresponding cumulative capacities:

$$C_{i,k} = \left(\frac{(1-b)}{a}\left(TC_{i,k}\right)\right)^{\frac{1}{1-b}} \quad (11)$$

This type of segmentation is shown in Figure 4. It is relatively insensitive to the variations of the $C_{k,max}$ and the number of segments, but it seems a good compromise and gives adequate and stable results. For a discussion of the influence of the segmentation procedure see numeral 4.3.2.1 below.

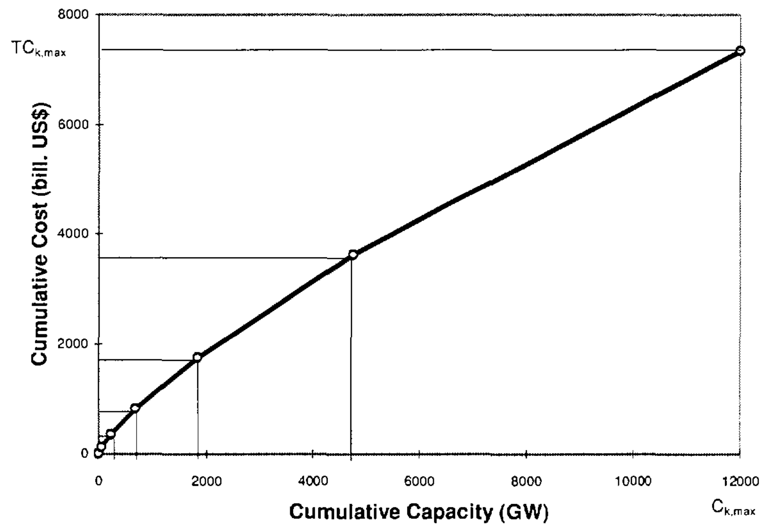

Figure 4. *Piece-wise approximation of the cumulative cost curve*

3.7 The first interpolation procedure

The basic idea of the MIP approach relies upon a procedure to interpolate a piece-wise linear function *f(x)* composed of N-1 line segments connected by N knot points (Sierksma, 1996). This procedure, which uses binary variables to express points on the piece-wise curve as convex combinations of adjacent knots in the curve, allows one to describe the stepwise function as an equivalent of several linear constraints that can be handled by an MIP model.

3.7.1 Interpolation of cumulative capacity

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

$$C_{k,t} = \sum_{i=1}^{N} \lambda_{k,i,t} \quad (12)$$

3.7.2 Interpolation of cumulative cost

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

$$TC_{k,t} = \sum_{i=1}^{N} \alpha_{i,k} * \delta_{k,i,t} + \beta_{i,k} * \lambda_{k,i,t} \quad (13)$$

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

With:

$$\beta_{i,k} = \frac{TC_{i,k} - TC_{i-1,k}}{C_{i,k} - C_{i-1,k}} \quad (14)$$

$$\alpha_{i,k} = TC_{i-1,k} - \beta_{i,k} C_{i-1,k} \quad (15)$$

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

Although the piece-wise representation is done directly on the cumulative cost curve, the examination of the resulting stepwise curve for the specific cost provides an idea of its accuracy. The equivalent specific cost (SC) for each segment corresponds to the coefficient $\beta_{i,k}$. Figure 5 presents the specific cost curve corresponding to the variable length segmentation described above. As mentioned, the parameters $C_{k,max}$ and N as well as the segmentation procedure affect the resulting piece-wise approximation of the non-linear learning curve and have to be defined carefully. For a discussion of their influence see numeral 4.2.3 below.

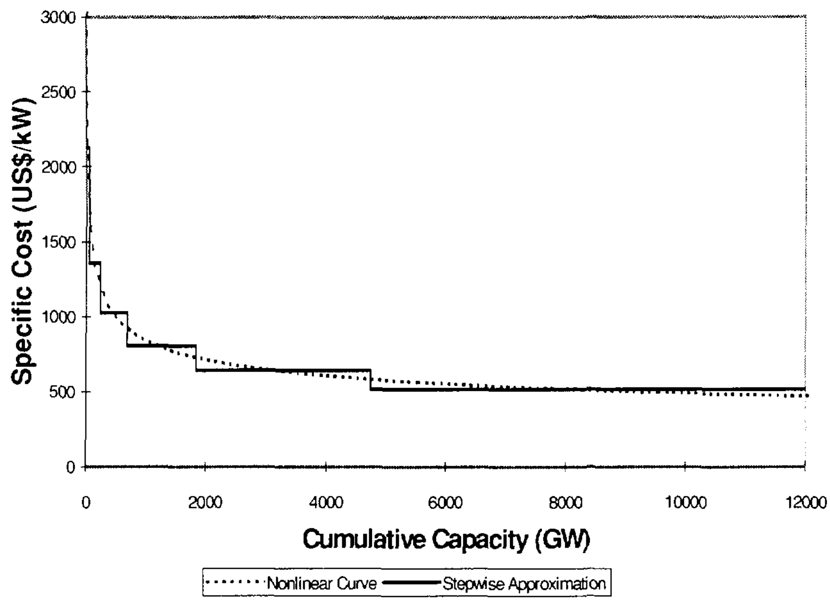

Figure 5. *Stepwise approximation of the specific cost curve - Variable length segments*

3.7.3 Logical constraints

The logical conditions regarding the control of the active segment of the cumulative curve are defined using the help of binary variables delta:

$$\begin{aligned} \lambda_{k,i,t} &\geq C_{i,k} * \delta_{k,i,t} \\ \lambda_{k,i,t} &\leq C_{i+1,k} * \delta_{k,i,t} \end{aligned} \quad (16)$$

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

3.7.4 Sum of delta variables to one

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

$$\sum_{i=1}^{N} \delta_{k,i,t} = 1 \quad (17)$$

3.7.5 Additional "unnecessary" constraints

Using the fact that experience must grow or at least remain at the same level, additional constraints may be added to the basic formulation. The basic rationale behind is that in the period t+1 the technology will either remain on the segment of the curve where it is located in the period t or move to a further one, but cannot go back to a previous one. Then, these constraints provide a relation between the binary indicator variables $\delta_{k,i,t}$ across periods, according to the sequence that must be followed, helping to reduce the solution time.

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

$$\sum_{P=1}^{i} \delta_{k,P,t} \geq \sum_{P=1}^{i} \delta_{k,P,t+1}$$
$$\sum_{P=i}^{N} \delta_{k,P,t} \leq \sum_{P=i}^{N} \delta_{k,P,t+1} \quad (18)$$

3.8 The second interpolation procedure

This formulation differs from the first one only in the interpolation of the cumulative capacity and cost and the definition of the corresponding logical constraints. An additional constraint regarding the summation of lambda variables, which have now a different definition, is also added. Only the expressions where a change is due are described. The others remain as described for the first one.

3.8.1 Interpolation of cumulative capacity

The cumulative capacity is expressed as a weighted summation of the breakpoints, where the weighting factors are the lambda variables. The number of lambda variables will correspond to the number of breakpoints specified (that is N+1).

$$C_{k,t} = \sum_{i=0}^{N} \lambda_{k,i,t} * C_{i,k} \ (19)$$

3.8.2 Interpolation of cumulative cost

The cumulative cost is also expressed in terms of the corresponding breakpoints weighted by the lambda variables.

$$TC_{k,t} = \sum_{i=0}^{N} \lambda_{k,i,t} * TC_{i,k} \ (20)$$

3.8.3 Sum of lambda variables to one

For every technology k and every time period t, force the sum of lambda to one:

$$\sum_{i=0}^{N} \lambda_{k,i,t} = 1 \ (21)$$

3.8.4 Logical constraints

For i=1, ...N

$$\left(\sum_{r=0}^{N}\lambda_{k,r,t}\right)-\lambda_{k,i-1,t}-\lambda_{k,i,t}+N\delta_{k,i,t}\leq N \tag{22}$$

This problem can also be formulated by using the so-called Special Ordered Sets (SOS). The $\lambda_{k,i,t}$ variables can be declared as SOS-2 variables[6] in order to exploit its special structure for purposes of computational efficiency (Williams, 1985). In that case, equations 21 and 22 are already implicit in the definition, the binary variables delta will not be used explicitly and, of course, the "unnecessary" constraints cannot be applied. This alternative, followed by Messner (1997), was not considered here.

[6] Special ordered Sets (SOS) are sets of non-negative variables that are required to sum to 1. The variables within a Type Two Special Ordered Set (SOS-2) fulfil the condition that at most two members of the set are positive and if these two are positive they have to be adjacent.

4. Some results from models with endogenous technological change

In this section, some analyses are presented with both the ERIS and MARKAL models. Although, primarily methodological insights are derived, some interesting results with policy implications are also outlined. The results presented here are drawn mainly from Kypreos and Barreto (1998a) and Kypreos and Barreto (1998b). Although, in some cases modifications to the data or the model runs were introduced, the basic conclusions reported in those papers still hold and are re-stated here.

First, the initial experiences with the ERIS Prototype are described deriving mainly methodological insights. Comparison between the LP (static), NLP and MIP solutions is discussed and the parameters affecting the MIP approach are examined. Also, an example with the two-stage stochastic model is presented. Then, a similar analysis with MARKAL is presented. Sensitivity to the progress ratio and the discount rate as well as the possibility of specifying a two-stage learning are discussed.

4.1 Description of technologies

The analyses have been concentrated in the global electricity generation market. Electricity constitutes one of the fastest growing sectors of the world energy system. Global energy trends towards an increasing use of more clean and more flexible end-use fuels signal a growing role for electricity in the future (IIASA-WEC, 1998). It is also an important contributing sector to CO_2 emissions (Ellis and Tréanton, 1998), where attractive potential exists to implement less carbon emitting generation options. The highly dynamic growth of the demand, together with the restructuring of electricity markets around the world, the mounting environmental constraints, huge capital requirements and the availability of primary resources will certainly exert a significant impact on the technological trajectory the system will follow in the future. Therefore, it is important to examine opportunities for the different competing technologies.

In this section, the main characteristics of the technologies considered in the exercises presented here are described. The basic parameters for the technologies are shown in Table 1. Cost figures are in 1998 US dollars[7].

Six technologies are considered to have a progress ratio lower than one: Solar photovoltaics, wind turbines, gas fuel cell, combined cycle gas turbines, advanced coal and new nuclear power plants.

[7] Unless specified otherwise, a discount rate of 5% is used in all calculations

Technology	Abbrev	Inv. Cost (US$/kW)	Fixed O&M (US$/kW/year)	Var. O&M (US$/kWyr)	Efficiency (Fraction)	Progress Ratio
Conventional Coal	HCC	1357	69	22.7	0.39	1
Advanced Coal	HCA	1584	67.5	23.6	0.45	0.94
Gas Steam	GSC	987	50.6	17.7	0.41	1
Gas CC	GCC	600	36.6	19.7	0.51	0.89
Gas Turbine	GTC	350	58.5	16.03	0.36	1
Gas Fuel Cell	GFC	2463	43.5	105.1	0.65	0.81
Oil Steam	OLC	1575	63.6	18.13	0.38	1
Nuclear	NUC	3075	114	5.91	0.34	1
New Nuclear	NNU	3400	114	5.91	0.36	0.96
Hydro	HYD	3562	49.5	3.9	0.70	1
Solar PV	SPV	4600	9.	39.4	0.1	0.81
Wind	WND	1035	13.5	26.3	0.33	0.88
Geothermal	GEO	3075	7.8	92	0.3	1

Table 1. *Main characteristics of electricity generation technologies*

Solar photovoltaics and wind turbines are emerging renewable options that have experienced a highly dynamic growth in the last years. In response to government incentives and support in several countries, wind turbines have been able to penetrate to a certain extent the global marketplace. However, although already attractive in some markets, the technology still has to consolidate itself as a competitive alternative and there are a number of concerns regarding reliability, land use, wind resource information, etc., that must be addressed. Nonetheless, interesting cost reductions and incremental performance improvements can be expected (Neij, 1999).

Solar photovoltaics has undergone significant improvements, constituting already a sound option for remote areas (Thomas et al. 1999). Although it still depends to a large extent on niche markets, in the last years the rapidly growing business has received the interest of several big companies and research activities have been intensified (Sweet, 1999). The technology is still very expensive for utility grid applications, but there is ample room for efficiency and cost improvements (Cody and Tiedje, 1997).

Gas fuel cell, on the other hand, is a technology mainly in the demonstration phase, but very promising for both transportation and stationary power applications. Small units of phosphoric acid fuel cells (PAFC), up to 200 kW, are being commercially available since the beginning on the 90's, being applied mainly for on-site co-generation (DOE/FE, 1996). Although also some MW-size units have been tested, some developers seem willing to favour small size units (up to 500 kW) for distributed stationary applications such as powering individual homes or commercial buildings (Lloyd, 1999). The fuel cell still has a long way to go to become cost-competitive, but in several applications it is beginning to be chosen due to their comparative cleanliness, high efficiency, silent operation, multiple fuel choice and grid independence. There is potential for gas fuel cell to conquer and expand niche markets and further performance improvements can be achieved.

Clean coal technologies, such as pressurised fluidised bed combustion (PFBC), atmospheric fluidised bed combustion (AFBC), and integrated gasification combined cycle (IGCC), are being demonstrated in several countries. They have already experienced significant advances and could provide important efficiency increases as compared to conventional coal-fired plants. Expectations about their future cost reductions have being positively changing in the last few years (Schrattenholzer, 1998)

The gas turbine has become one of the most competitive electricity generation alternatives due to its low investment costs, short building times, high efficiency, lower emissions and modularity. It has even been considered as the emerging technological paradigm in electricity generation (Islas, 1999), and it is expected to rapidly increase its share in the electricity market. Further technical improvements, however, would depend strongly on the development of new materials. Learning has been considered here for the combined cycle gas turbine.

Although the future of nuclear power appears uncertain in several countries and issues concerning safety, public perception and disposal of spent fuel still have to be solved, new designs of nuclear power plants have emerged, which are expected to the safer and less costly. In addition, the nuclear option could be attractive if significant CO_2 emission reductions must be achieved. First-of-a-kind units of the newly designed plants would certainly be expensive, but there are expectations that experience with them may lower construction and operation costs (EIA, 1998).

Figure 6 presents the corresponding learning curves used in this analysis. For the segmentation with the MIP approach, a maximum cumulative capacity of 6000 GW was considered for all the learning technologies[8].

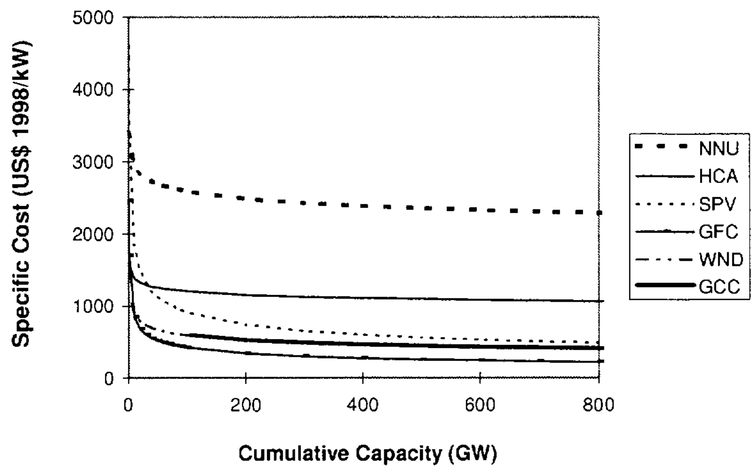

Figure 6. *Learning curves for different technologies*

[8] This capacity was not acting as an upper bound for anyone of the technologies included in the database.

Although no attempt is made to fully justify the progress ratio values used, they are within the usual ranges reported in the literature. There is uncertainty concerning learning parameters and technology characteristics. Therefore, the results should be regarded much more as what could happen if progress could be sustained at such pace. A further question would be which actions should be required in order to ensure that these trends take place.

4.2 First experiences with the ERIS model prototype

The ERIS model prototype has been created within the TEEM project as a tool to test different formulation approaches and solution methods, regarding endogenous incorporation of technological change in energy models. It provides a straightforward way of testing new concepts before translating them to more complicated models and allows to assess their advantages, disadvantages and implementation difficulties.

The development of the model has been a joint effort between several partners. The original prototype was formulated by IIASA (Messner, 1998) and coded and tested by the NTUA (Capros et al. 1998a) as a Linear Programming (LP) version and a Non-linear Programming one (NLP), which included a non-linear formulation of learning curves. The prototype was extended by PSI to include stochastic and risk aversion options and more general constraints (Kypreos, 1998). NTUA reformulated the Non-linear Program as a Mixed Complementarity Problem (MCP), including also the stochastic treatment for this one (Capros et al., 1998b). In order to guarantee global optimal solutions, PSI implemented the Mixed Integer Programming (MIP) formulation of learning curves (Kypreos and Barreto, 1998a). A further extension of the model including a regional index and trade of energy carriers and emission permits has been implemented at PSI and used in Barreto and Kypreos (1999) for post-Kyoto analyses. A detailed description of the model may be found in Kypreos et al. (1999).

ERIS represents the global electricity market supplied by a number of electricity generation technologies. The linear model underlying the prototype is formulated on the basis of a small MESSAGE [9] model. A simplification is made concerning interpolation of values between periods: the activity over a period is assumed to be constant, i.e. a step function is used instead of linear interpolation of the values. All variables in the linear model refer to average annual values in the period. The time horizon used for the analysis here is 1990 to 2050 with 10 year time steps (including the 10 years after 2050).

The linear model is completely static, i.e. all parameters are constant over time[10]. The non-linear and MIP models have reduction factors for the investment costs as a function of the

[9] MESSAGE is the energy optimisation model developed at IIASA (Messner and Strubegger, 1995)

[10] However, the model is formulated in a general way and with very small changes it can be specified as a dynamic linear program and the time horizon extended. Also, an endogenous specification of other parameters such as O&M costs or efficiency could be incorporated in the future.

cumulative installations. Model runs for the ERIS prototype were done using the CPLEX 6.0 solver for LP and MIP problems[11] and the MINOS5 solver for NLP problems.

The comparative results of the ERIS model prototype presented in this section allow to illustrate the impact of technological learning in the structure of the simplified global electricity system used as example[12]. The demand corresponds to the scenario B ("middle-course") of IIASA-WEC(1998). For the MIP segmentation, eight segments were considered for all the technologies. First, the comparison between the static LP, NLP and MIP solutions of the ERIS model is presented. Table 2 summarises the objective values for a Business-as-Usual and a CO_2 constrained scenario using the different formulations.

For the MIP results, as an indicative of the error involved in the approximation, the following procedure reported by Mattsson (1997) is used. After the optimisation, the discounted cost of the MIP solution is computed again using the original non-linear curves to calculate the corresponding investment costs for the learning technologies, thus providing the correct estimation of the cost. The difference between this value and the original MIP objective value gives a measure for the accuracy of the MIP approximation (in parenthesis in Table 2). When the difference is small the approximation may be considered adequate.

Objective value	BaU	CO_2 reduction
LP	8759498.14	8849840.0
NLP	8647366.39	8683280.8
MIP	8638750.95 (0.2%)	8668759.98 (0.19%)

Table 2. *Objective function of the different alternatives*

The solutions of both models incorporating learning, NLP and MIP, are structurally different from the ones obtained using the LP approach. The MIP formulation is able to provide lower objective values than the NLP one. In some cases the local optimum solutions found with NLP model provided a technology mix similar to the MIP one, but in other cases the structure of the energy system was significantly different.

Figure 7 presents a comparison of the global generation mix for the year 2050. Figure 8, Figure 9 and Figure 10 present the electricity generation along the time horizon with each version of the model for the CO_2 constrained case. In the LP model the system relies mainly upon combined cycle gas turbines to supply the demand. Conventional nuclear plants and, to a less extent, wind turbines are the main contributors to fulfil the CO_2 target. In the NLP model, gas combined cycle still constitutes the main supply option. Conventional nuclear technology is displaced by an increase in wind turbines output and, to a less extent, new nuclear plants. In the MIP model, solar photovoltaics is massively

[11] For the MIP problems, following the recommendation of Mattsson (1997), the VARIABLESELECT parameter , used to set the rule for selecting the branching variable at the node selected for branching (ILOG, 1997), was set to 'strong branching'.
[12] The results of this example have only illustrative purposes.

introduced and the gas combined cycle plays a much more reduced role. By the end of the time horizon, solar PV, together with wind turbines and advanced coal plants, have experienced a significant growth.

The differences in the structure of the energy systems resulting from the LP and the NLP and MIP learning versions are evident. The models with learning favour, under the assumed learning patterns, the introduction of new technologies, hardly considered by the LP-static model. Up-front investments are performed in order to render them competitive in the long term. There is also a clear difference between the local optimum obtained in this case with the NLP model and the global optimum obtained with the MIP one.

When the NLP is solved again, using as restarting values those corresponding to the MIP solution, better optima for several of the NLP problems were found. In several cases, this restarted NLP solution was indistinguishable from the MIP one. Table 3 presents the new NLP optima and the percentage reduction respect to the previous ones.

	BaU	Stabilisation
Objective value	8642374.3	8674556.3
% reduction	0.06%	0.1%

Table 3. *New NLP objective values if restarting from MIP*

It must be mentioned that for some of the particular tests with this small scale problem, the NLP model (without restarting) was already able to find very good solutions. However, other experiences using MARKAL (Kypreos and Barreto (1998d) or Seebregts (1998) with a large scale database) did not provide such results, with the NLP problem even behaving in an unstable way in some cases.

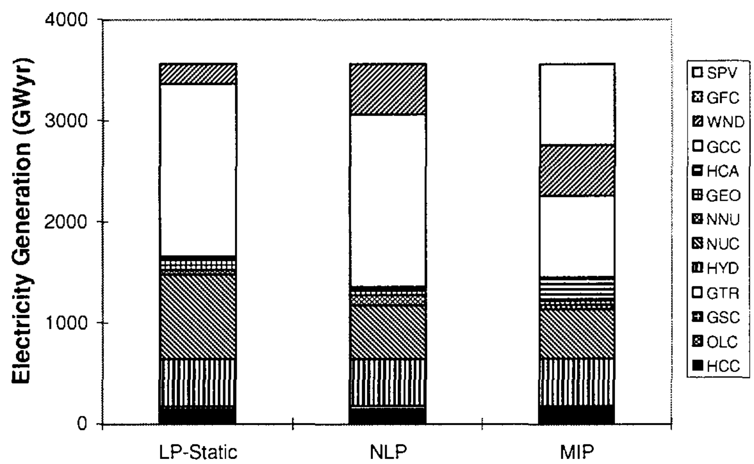

Figure 7. *Comparison of electricity generation in 2050. CO_2 constrained scenario*

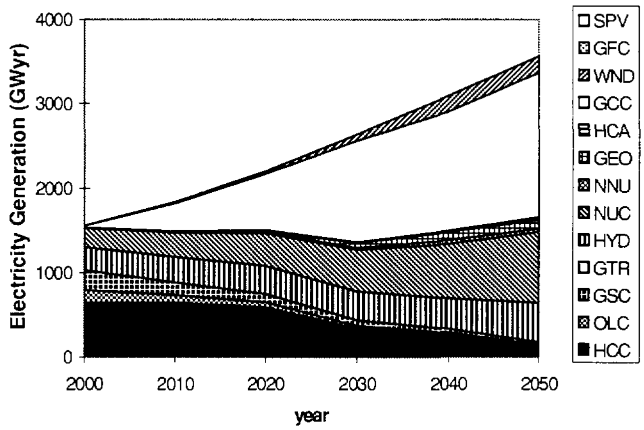

Figure 8. *Electricity generation. LP model. CO_2 constrained scenario*

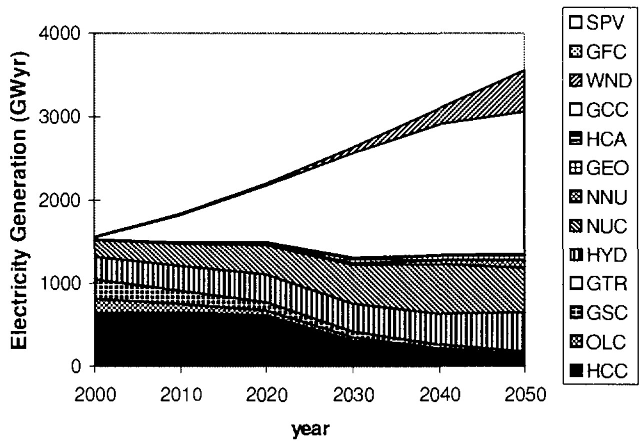

Figure 9. *Electricity generation. NLP model. CO_2 constrained scenario*

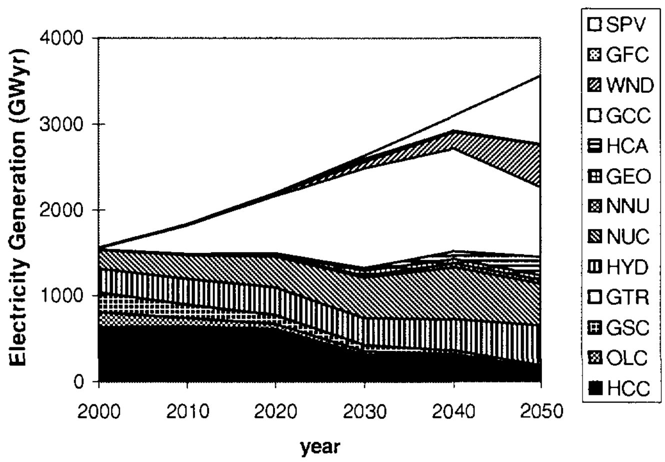

Figure 10. *Electricity generation. MIP model. CO_2 constrained scenario*

4.2.1 Evolution of the specific cost

The evolution of the specific costs when using the MIP piece-wise formulation is examined, using as example the solar photovoltaics technology for the CO_2 constrained scenario. As explained before, the linear approximation is carried out directly on the total cumulative cost curve. However, one is also interested in the evolution of the specific cost, as it provides valuable information about the progress experienced by the learning technologies along the time horizon.

Figure 11 presents the evolution of specific cost for solar photo-voltaics along the time horizon, computed as the quotient between the investment costs $IC_{k,t}$. and the new installed capacity per period ($INV_{k,t}$). As a comparison, the specific cost, obtained using the continuous expression of the learning curve for the same cumulative capacities, is also presented.

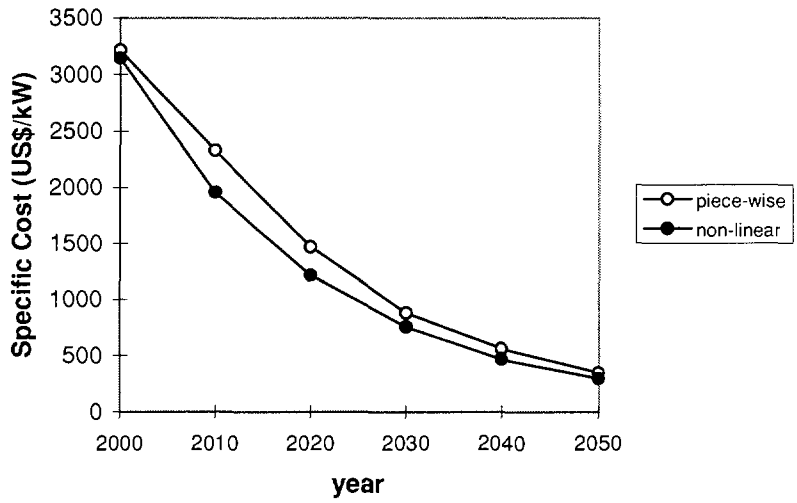

Figure 11. *Evolution of specific cost for SPV. Piece-wise and continuous curves.*

By the end of the time horizon, the investment cost of the solar photovoltaics technology in this scenario has reached 340 US$/kW. This behaviour has raised the question, whether the cost reduction of some learning technologies should be limited, for instance providing a lower bound for the specific cost, in order to avoid excessive cost reductions. This lower bound would probably correspond to the expected cost of the technology in its mature stage. It must, however, be supported by studies of the cost structure and specific potential for cost reductions in the different components. This "floor" cost will provide a saturation effect of the learning process additional to the normal saturation of the curve itself.

4.2.2. Stochastic ERIS

To address the climate change issue or other environmental and economic problems, one has to take into account the various uncertainties related to it. A first method to do so is the scenario analysis. This method does not deliver a single set of recommendations but it is possible to identify robust technologies as key technologies for making investments in the energy sector or for R&D support.

An alternative approach is to consider explicitly uncertainty within the model, to define the decisions that have least regret under all outcomes of uncertainty. These robust decisions, which constitute a hedging strategy, can be selected with a traditional multi-stage stochastic programming model. To each scenario s=1,...S, a subjective probability p_s is associated. Uncertainty is assumed to be resolved by a certain point in time t_r. The decision variables can be grouped into two categories: x_1, the decisions to be determined before the resolution of uncertainty, and $x_{2,s}$, those to be defined afterwards depending of the state of the world that finally occurs.

This problem corresponds to a two-stage stochastic problem, as illustrated by the decision tree in Figure 1. The decisions belonging to the first stage are common to the S scenarios and constitute the hedging strategy. This strategy is defined by minimizing the expected costs of all the different states of the world. The two-stage stochastic formulation can thus be expressed as:

$$\begin{cases} \text{Min} \left[c_1^T x_1 + \sum_{s=1}^{S} p_s c_2^T x_{2,s} \right] \\ s.t. \\ \qquad A_0 x_1 \le b_0 \\ \qquad A_1 x_1 + A_2 x_{2,s} \le b_s, \quad s = 1,\dots,S, \end{cases} \tag{23}$$

The constraints are derived from the deterministic formulation of the model. They ensure the feasibility of decisions and link first stage decisions (x_1) with second stage decisions ($x_{2,s}$). This formulation, where uncertainty appears only on the right-hand-side b_s, corresponds to a decision tree describing, for instance, alternative CO_2 emission reduction policies (Figure 12).

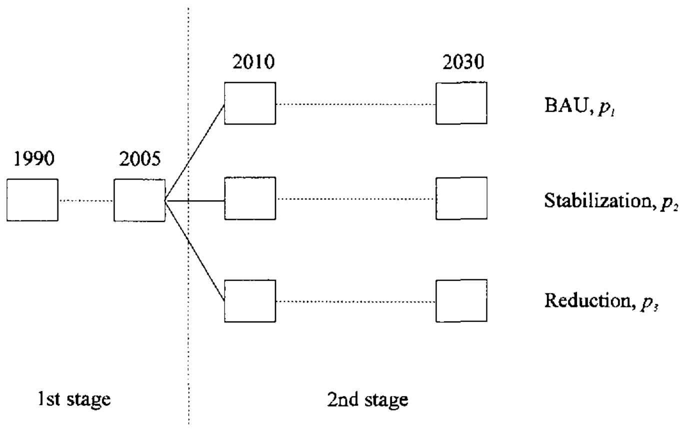

Figure 12. *Decision tree for the two-stage stochastic problem*

The ERIS code has been extended by PSI (Kypreos, 1998) to include stochastic and risk aversion options. These options are defined for the linear, non-linear and MIP formulations. Their introduction into the ERIS prototype is based on the work done previously by Van Geffen (1995) for a reduced version of the MARKAL model. NTUA has also incorporated this stochastic approach to the MCP version of the model (Capros et al. 1998b)

The stochastic treatment was introduced for:

- CO_2 emission reduction targets. In this case, technologies assume a certain learning behavior.
- Progress ratio of learning technologies. The model selects future technologies that assume uncertain progress ratios with a given probability.
- Electricity demand
- A combination of the above options with the restriction that uncertainty is resolved simultaneously.
- The risk aversion option minimizes the expected cost together with the (positive) deviation of the different states from the expected cost.

For simplification, the stochastic ERIS is defined as a 2-stage stochastic problem where the uncertainty on all the stochastic parameters is resolved simultaneously at a pre-specified date. If uncertainties in any of those parameters, or the learning uncertainty for different technologies, were required to be resolved at different points in time, the formulation would have to be extended to a multi-stage program.

Here, as an example with the two-stage MIP stochastic version of ERIS, the effects of uncertainty in emission limits are examined. Three emission scenarios were considered: an unconstrained Business-As-Usual scenario (BaU) and two constrained ones (denominated red A and red B). For simplicity, all states of the world are considered with the same probability of occurrence. The uncertainty is resolved in the year 2030. The learning parameters were assumed common to these three scenarios.

The hedging path for emissions is presented in Figure 8, which compares the deterministic and stochastic emission trajectories. In this particular example, the emission profile of the unconstrained BaU deterministic case already shows a pattern that may arise when endogenous technological learning is present. Emissions may be substantially reduced in the long term due to the sole dynamics of technological change even in the absence of an emissions constraint (Grübler, 1998). The stochastic model, however, adopts a policy of stronger early CO_2 reduction, following a trajectory well below the BaU deterministic case. Uncertainty in the emission target drives to an earlier stimulation of technological learning in order to prepare for future contingencies. The early penetration of low-carbon technologies, which constitutes the hedging strategy in the first stage of the stochastic case, drives to much lower emission profiles in the second stage, compared to the deterministic cases, for those scenarios (BaU and Red A) progressively less affected by the strongest constraint in the second stage.

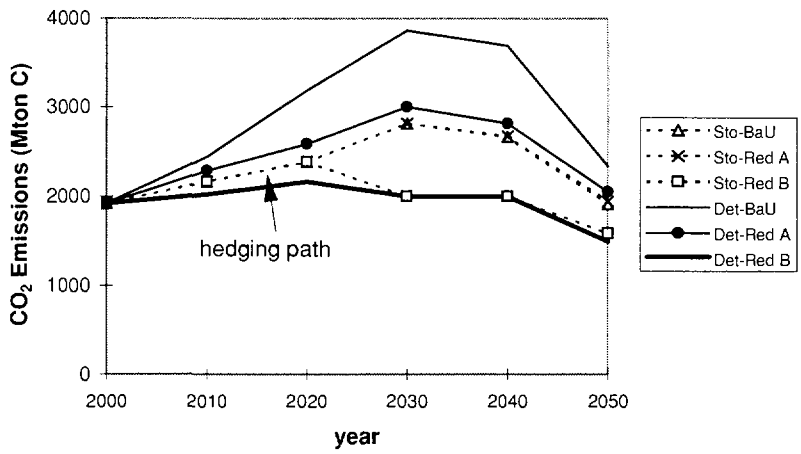

Figure 8. *Global CO_2 emission trajectories. Deterministic Vs stochastic cases*

It is important to analyse further the combination of environmental and economical uncertainties and technological learning. One could examine, for instance, the reciprocal effects of learning and hedging against global warming in the energy systems. A hedging strategy, calling for early abatement efforts will constitute an incentive for new environmentally compatible technologies, which could then begin to move along their learning curves. As they progress to reach competitiveness, their accumulated learning will contribute to reduce the costs of the abatement actions. Thus, the starting of the abatement itself (not necessarily aggressive mitigation actions) would become an important factor to induce the required technological change, which is in turn necessary to reach the transition at lower economic costs (Grubb, 1997, Grübler and Messner, 1998).

4.2.3 Influence of some parameters on the MIP approach

The accuracy and efficiency of the MIP linearisation is affected by several factors. Here, the influence of the segmentation procedure, the maximum cumulative capacity and the number of segments is analysed. The discussion here has been adapted/adopted from that in Kypreos and Barreto (1998a).

4.2.3.1 Segmentation procedure

The segmentation procedure has effects on the computation and must be defined carefully. An efficient segmentation has to be defined in accord to the form of the curve. Here, a comparison is made between a simple rule with the breakpoints in the cumulative cost axis equally spaced and the rule with variable length segments described in the numeral 3.6 and used in the model runs.

The rationale for the variable length segmentation procedure comes from the shape of the curve itself. The cost reduction is very significant for the first installed units, but afterwards the learning effect saturates. Therefore, one will expect a higher estimation error for the first segments. It seems reasonable to use a segmentation procedure with shorter segments at the beginning and increasingly longer segments afterwards, in order to obtain a better representation for the first region of the curve.

Figure 13 presents the resulting stepwise specific cost curve when using this segmentation. It provides better estimates for the first segments and fits better to the shape of the curve. It is relatively insensitive to the variations of the $C_{k,max}$ (see Figure 15) and the number of segments, but it seems to be a good compromise. In fact, the increase of number of segments will basically add a new point for the first region of the curve, improving the estimate of the first segments, but the other ones will not be significantly changed. The decrease of $C_{k,max}$ will provide a higher estimate for the first segments.

As the estimated specific cost corresponds to the slope of every linear segment of the cumulative cost curve, the first segment has a much lower value than the starting cost in the non-linear curve, thus underestimating the cost for the first units. This effect is more significant for technologies with higher learning rates. The segmentation plays also here a significant role (seeFigure 13).

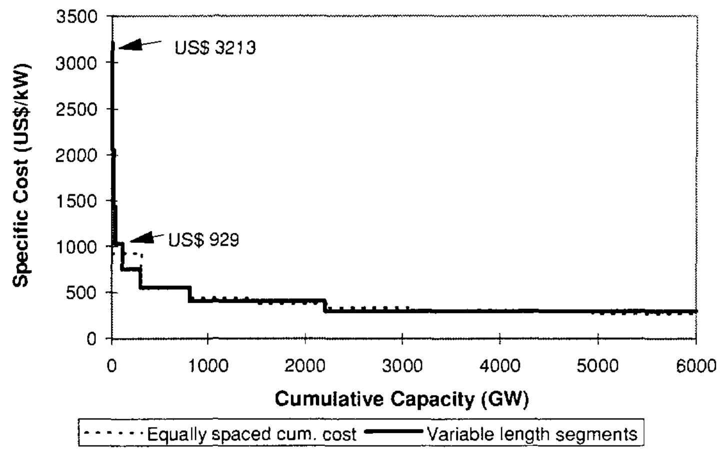

Figure 13. *Alternative variable-length Vs equally spaced cumulative cost segmentation procedures*

Other segmentation forms can be used. However, there will always be a trade-off between the accuracy of the representation of the different zones of the curve. A segmentation based on the logarithm of the cumulative cost is used in Seebregts et al. (1998). Mattsson (1997) reports a procedure intended to achieve a more efficient segmentation, using two different values of maximum capacity to define the breakpoints.

4.2.3.2 Number of segments

The number of segments influences the precision of the approximation and the solution time. A higher number of segments may provide a better representation but the time for solving the model will increase as the number of binary variables increase.

As the cumulative cost curve is concave, the linear approximation provides values under the real cumulative costs, driving to underestimation of the investment costs. Due to this, the MIP solution corresponds to a lower bound for the global optimum of the non-linear problem. As the number of segments is increased, the gap is reduced, deriving in higher estimates for the investment costs, which result in an increase of the objective function.

As an example, Table 4 presents the changes on the objective function for different number of segments for the CO_2 constrained scenario (the variable length segmentation is used and all technologies have the same number of segments) .In these particular tests, the variation on the number of segments within this range did not alter the structure of the solution.

Number of segments	Value of Objective Function	% change
5	8663690.62	-0.06%
6	8666096.73	-0.031
7	8667765.58	-0.011%
8	8668759.98	0%
9	8669231.11	0.005%
10	8669435.90	0.008%

Table 4. *Variation of the MIP objective value with the number of segments*

4.2.3.3 Maximum cumulative capacity

The choice of the maximum cumulative capacity ($C_{k,max}$) is also one of the determinants of the segmentation. For the same number of segments, a lower $C_{k,max}$ value may provide a better representation. The partition will be such that the corresponding steps will have higher specific costs, although the intervals of cumulative capacity are smaller (see Figure 14 and Figure 15 for comparative examples).

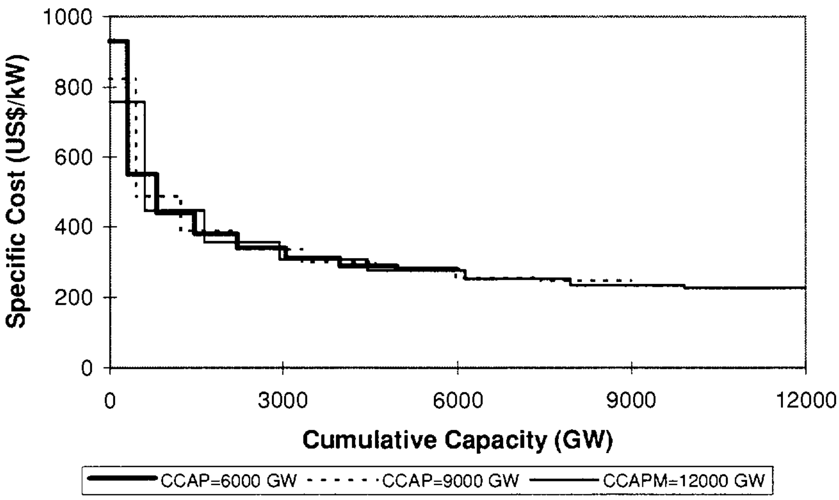

Figure 14. *Specific cost segmentation for different maximum cumulative capacities. SPV Technology. Equally spaced cumulative cost rule.*

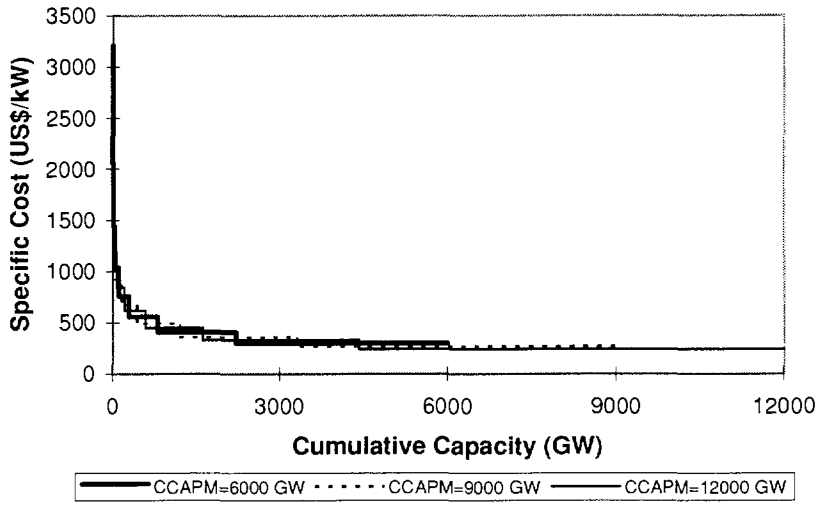

Figure 15. *Specific cost segmentation for different maximum cumulative capacities. SPV Technology. Variable length rule*

Table 5 shows the changes in the MIP objective function when the $C_{k,max}$ parameter is modified. Percentage increases are reported respect to the situation with $C_{k,max}$=6000 GW, which was used for the previously presented model runs.

$C_{k,max}$	BaU		CO_2 stabilisation	
	variable length	equally spaced TC	variable length	equally spaced TC
6000 GW	8638750.9	8624093.8	8668759.9	8654089.0
9000 GW	8637268.6	8617419.9	8668719.9	8654517.2
% change	-0.017	-0.077	-0.0005	0.005
12000 GW	8639565.6	8614437.7	8669990.5	8641479.1
% increase	0.01	-0.112	0.014	-0.146

Table 5. *Variation of the MIP objective value with* $C_{k,max}$

The installations and output of a given technology may be affected when changing $C_{k,max}$. As a result of the higher specific cost steps when $C_{k,max}$ is lower, investments on a particular technology could be lower or occur later. However, it is not easy to determine what the exact effect will be and its magnitude depends also on the way the curve is segmented. Some segmentation patterns are more sensitive than others. Figure 16 and Figure 17 present the electricity generation mix in the year 2050, when different values of cumulative capacity are specified, under the two segmentation rules described above. For this case, the variable length segmentation method provided a more stable approximation. In this exercise, the basic structure of the solution was not significantly altered when $C_{k,max}$ was modified.

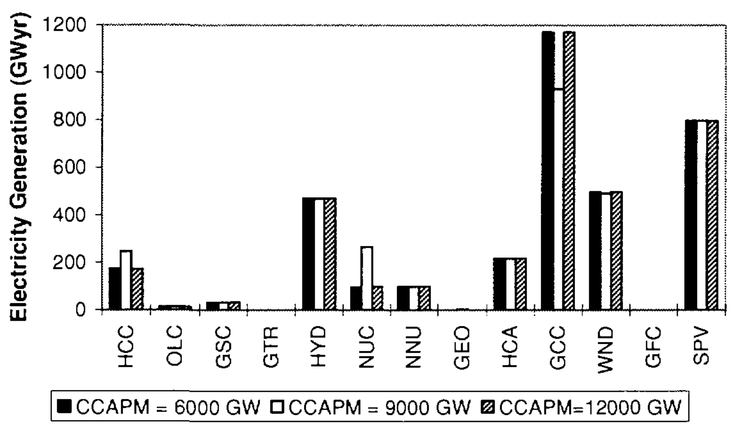

Figure 16. *Electricity generation mix in 2050. Different $C_{k,max}$. Equally spaced cumulative cost segmentation*

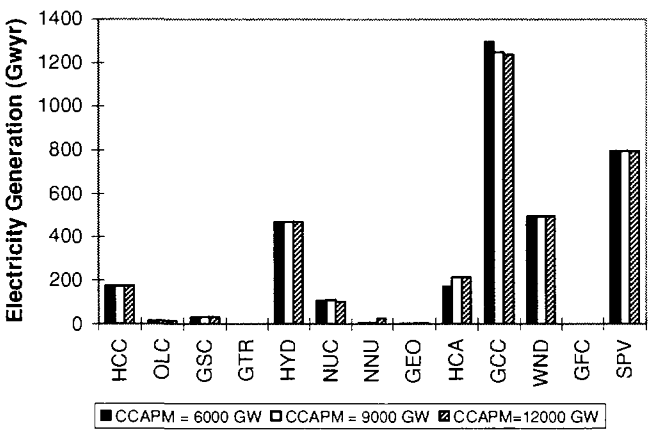

Figure 17. *Electricity generation mix in 2050. Different $C_{k,max}$. Variable length segmentation*

The variations may not be particularly significant but they still exist. In fact, the sensitivity of the solution to the $C_{k,max}$ (and to other parameters) also depends on whether the learning technology is marginally used or not. Marginal technologies are much more sensitive to variations On the other hand, when a given learning technology is sufficiently attractive, such that it is installed along its maximum growth constraint due to the "lock-in" effect, moderate variations of the parameters will barely affect its installed capacity or output. Nevertheless, it is important for the analyst to bear in mind the applied assumptions.

Therefore, sensible values have to be assigned for $C_{k,max}$. Of course, the ultimate criterion corresponds to the estimated potential for a certain resource or technology according to technical, economic and environmental criteria but, below this upper bound, a convenient value has to be chosen which fits to the particular case conditions. A starting reasonable value may be used for the first run and, according to the evolution of the technology, it could be adjusted for subsequent ones. It should be taken into account, that $C_{k,max}$ implies an upper bound for the capacity of the technology. A value which is sufficiently high for a reference scenario may not be adequate for another scenario where the same technology has a higher penetration. Therefore, the chosen value should be consistent across the different scenarios in order to keep the same piece-wise cost approximation.

4.3 A simple global electricity MARKAL model with endogenous learning

MARKAL is a dynamic linear programming bottom-up model for energy systems (Fishbone and Abilock, 1981), developed by the Energy Technology Systems Analysis Programme (ETSAP)[13] of the International Energy Agency (IEA), and widely used for national and multi-national analysis in a number of countries. It is a technology-oriented model. That is, it allows a rich representation of supply and demand technologies in the energy systems, and helps to identify future cost-effective technological options and assess their role, under different system conditions (e.g. the fulfilment of environmental restrictions). Incorporation of technological learning is an important step to improve the consistency of mechanisms of technological change in the MARKAL family of models. As mentioned before, following the same formulation used in the ERIS model prototype, learning curves were also incorporated in the MARKAL energy optimisation model (Kypreos and Barreto, 1998b)[14].

Using the same technological database described above, some exercises performed with MARKAL with endogenous learning are presented here. The analysis in this section is based in Kypreos and Barreto (1998c). However, as the database is different, the role of different technologies may change. As before, the simplified system examined here represents the global electricity market and the demand for electricity corresponds to the IIASA scenario B (IIASA-WEC, 1998). In this exercise, competitiveness of different generation alternatives is examined, comparing the MIP learning solution with the static Linear Programming model (LP). Sensitivities for the learning rates are performed and the inclusion of a two-stage learning approach is discussed.

Two scenarios are considered. A Business-As-Usual scenario (BaU) represents the reference development. A CO_2 stabilisation scenario (Sta) imposes a constant 5% reduction from the 1990 level of CO_2 emissions from 2010 onwards[15]. Eight segments are used for the piece-wise approximation of all the learning curves. A maximum cumulative capacity ($C_{k,max}$) of 6000 GW is used for all the technologies. Maximum growth constraints for the capacity are used to control the penetration of technologies. The gas fuel cell and solar PV are allowed to grow at maximum 15% per annum. The other learning technologies have a growth rate of 10% per year.

[13] The ETSAP program, in its Annex VII (1999-2001), will concentrate activities in post-Kyoto related analysis. Therefore, methodological improvements in the handling of the technology variable are particularly important regarding the policy insights than can be derived from this kind of studies.
[14] The code is presented in Appendix 1
[15] This is, of course, a very strong constraint for the electricity system alone, and it is used here only to illustrate the response of the model.

4.3.1 Static linear programming Vs MIP learning

The model outcomes of the linear programming MARKAL with constant investment costs for the electricity generation technologies and the MIP model with the reference learning conditions are compared here.

Figure 18 presents the evolution of the electricity generation mix in the Business-As-Usual scenario for the static Linear Programming (LP) and the MIP-learning models. There are significant differences in the structure of the resulting energy systems. By the end of the horizon, in the LP model the electricity is provided mainly by coal (conventional and advanced) and gas-fired combined cycle plants, which becomes the dominant technology by 2050. Wind turbines are already competitive and penetrate the market. In the learning case, reliance on coal technologies is lower, while wind turbines and solar PV, have a higher contribution. Already in the BaU scenario the MIP learning model finds cost-effective the introduction of solar photo-voltaics not considered by the static-LP approach.

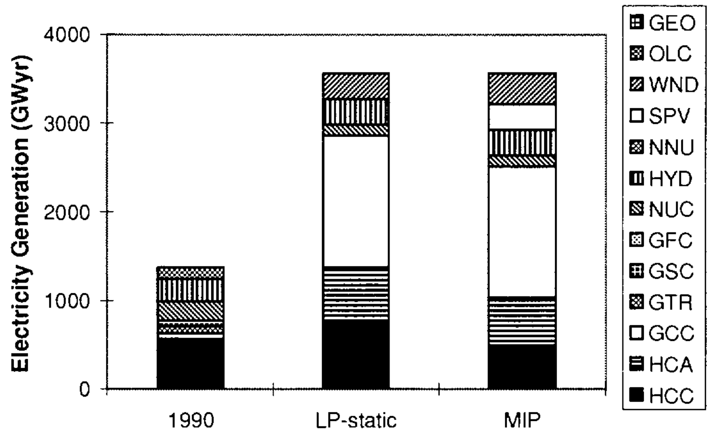

Figure 18. *Generation mix for the BaU scenario in 2050*

A more detailed view of the electricity generation obtained with the MIP model for the Business-As-Usual scenario (BaU) is presented in Figure 19. Conventional coal is still a very important generation technology, declining by the end of the horizon when new technologies have grown enough to make their contribution noticeable.

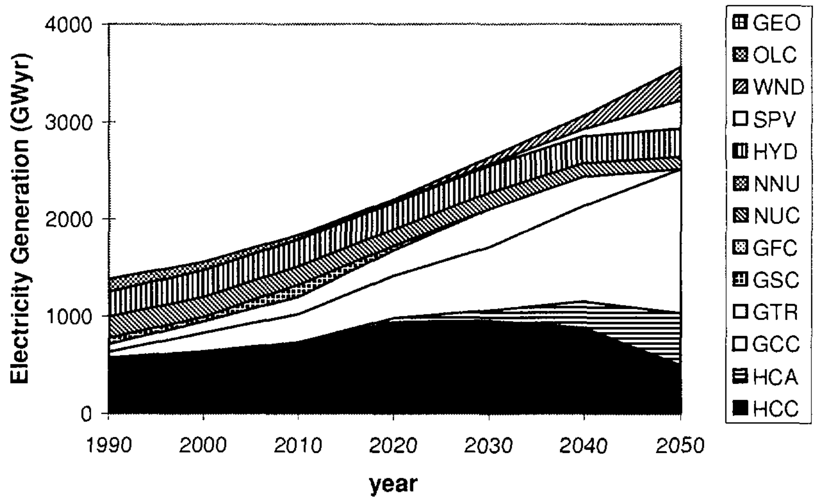

Figure 19. *Electricity generation - MIP Model - BAU scenario*

Figure 20 presents the comparison of the corresponding emissions in the BaU scenario and the CO_2 target imposed. Due to the introduction of new, cleaner technologies, the emissions for the MIP-learning model in the BaU scenario are below the ones for the static-LP model. As noticed before when discussing the first experiences with ERIS, this is an interesting result arising from the presence of endogenous technological learning. That is, particular technological trajectories chosen by the model may drive to reduction of emissions without the imposition of an exogenous constraint.

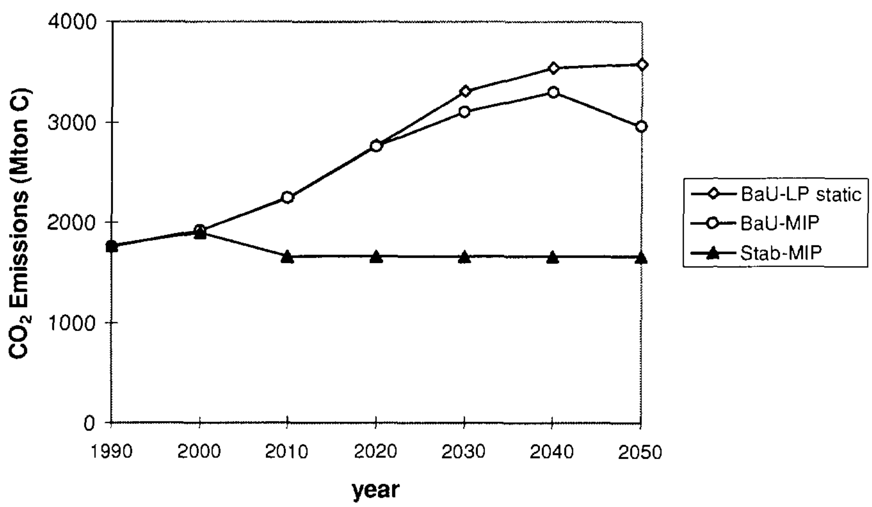

Figure 20. *Comparison of CO_2 emissions. LP static Vs MIP*

Figure 21 presents the comparison between the static-LP and the MIP-learning evolution of the electricity generation mix for the stabilisation scenario (Sta) in 2050. In the LP case, the system relies on gas combined cycle plants, conventional nuclear plants and wind turbines for fulfilling the target. The MIP learning model provides a more diversified system. In addition to the mentioned technologies, Solar PV, already growing at the maximum growth rate in the BaU case, gas fuel cells and new nuclear power plants are also introduced. In both cases, the gas combined cycle turbine becomes the dominant technology and coal generation is almost phased out by the end of the horizon.

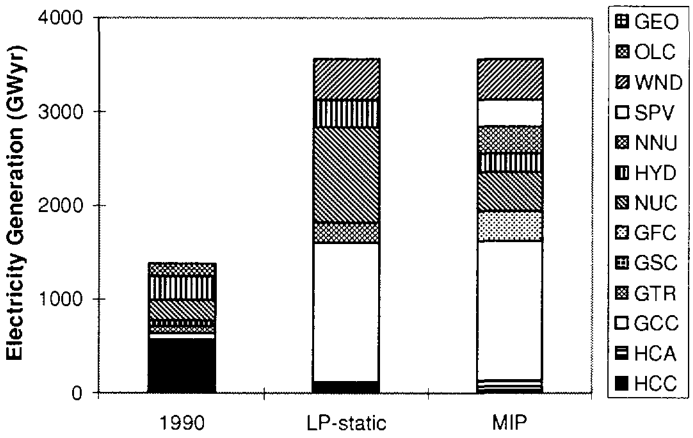

Figure 21. *Generation mix for the stabilisation scenario in 2050*

A more detailed view of the electricity generation obtained with the MIP model for the stabilisation scenario (Sta) is presented inFigure 22.

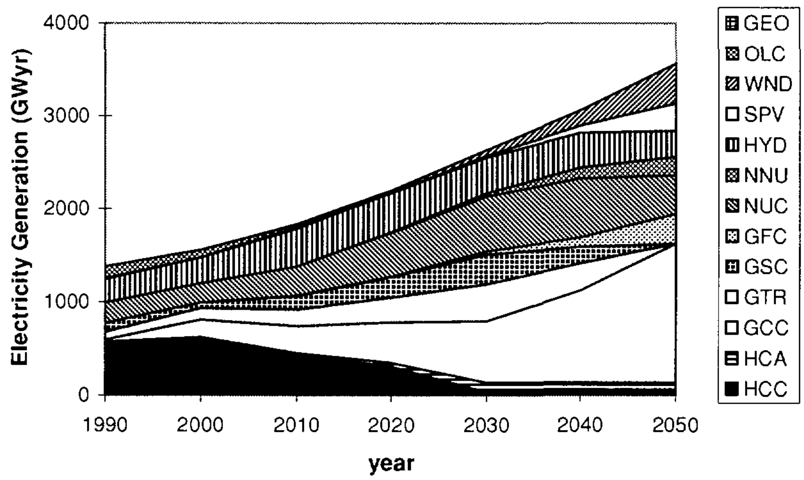

Figure 22. *Electricity Generation - MIP Model- Stabilisation scenario*

Another interesting comparison is the total discounted system cost. Cumulative investments are reduced in the endogenised learning case as compared to the static-LP one. A comparison of the mitigation costs, computed as the difference between the total system cost for the stabilisation scenario and the cost for the BaU scenario reveals that learning provides a reduction of 9.1% with respect to the LP-static case. This is an interesting fact, in agreement with the statement that earlier investments on new low-carbon or carbon-free technologies, although more expensive now, could prove beneficial in the long run, driving to lower costs of CO_2 abatement in the global energy system.

Scenario	LP-static	MIP-Learning	% Reduction
BaU	15099313	14934098	1.1
Sta	15992757	15745840	1.54
Mitigation Cost	893444	811742	9.1

Table 6. *Comparison of total discounted system cost (Million US$ 1998)*

4.3.2 Sensitivity to the progress ratio

Technological learning processes are significantly uncertain (Grübler, 1998), and the progress ratio remains one of the key, and most sensitive, assumptions for the endogenisation of learning curves in energy planning models. Historical estimates depend on data sets, time span and performance indicators used (Schrattenholzer, 1998). It is also very difficult either to ensure that the observed trends will continue in the future or that new developments will cause an alteration of the learning trajectory. The technology could reduce its learning rate as it approaches the commercial stage or this may be increased, for instance by higher R&D expenditures or breakthroughs in generic technologies affecting its development. Seebregts et al. (1998) discusses a number of issues that may affect the technology development and the derivation of a consistent progress ratio.

Due to the uncertainty, it is advisable to conduct sensitivity or stochastic analysis. Here, some sensitivity analyses are carried out for the system presented above. Stochastic analysis for uncertain learning rates has been performed for ERIS (see numeral 5.5.3 below) and could also be incorporated into MARKAL.

The sensitivity values for the progress ratio are presented in Table 7. For the Advanced Coal and New Nuclear technologies, it was considered as a sensitivity the case where no learning exists, given that these technologies are subject to environmental and safety concerns that may prevent them to achieve cost reductions[16]. For each run, the progress ratio of only one technology was modified. A comparison of the resulting electricity generation per technology is presented in Figure 23.

	Lower	Reference	Upper
Advanced Coal	0.88	0.94	1.0
Gas CC	0.84	0.89	0.94
Gas Fuel Cell	0.75	0.81	0.87
New Nuclear	0.92	0.96	1.0
Solar PV	0.72	0.81	0.85
Wind	0.81	0.88	0.94

Table 7. *Sensitivity values for the progress ratio*

[16] In fact, this has been the case for conventional coal and nuclear power plants. Mounting pressures to mitigate environmental impacts and improve safety have produced an increasing cost trend (Neij, 1999). Technological learning, in this case, has manifested itself in other performance indicators but not cost. However, new technologies may experience a different dynamics.

Solar PV was already attractive under the previous conditions both in the stabilisation and the BaU scenarios, growing along its maximum growth constraint. If progress ratio is decreased (i.e. faster learning), the technology will also grow along its maximum growth constraint. When the progress ratio is increased to 0.85, the technology is not installed at all under the unconstrained scenario. A progress ratio of 0.85 is not attractive enough and the technology, not being forced into the solution by a CO_2 constraint, is "locked-out" from the system. However, it grows again at maximum under the constrained scenario.

No significant variation resulted in the penetration of the wind turbine and the gas combined cycle under the range of progress ratios considered here. This is not surprising given that these technologies were already competitive even in the static-LP model (no learning). They are robust options for both the learning and the non-learning model.

The gas fuel cell, on the other hand, is more sensitive. The technology was not competitive for the BaU, with PR =0.81. An increase of PR to 0.87, makes it even less competitive. When progress ratio is decreased to 0.75, the technology is introduced in the BaU situation. In the CO_2 constrained case, the technology grows along the constraint for the three progress ratios considered.

Advanced coal and new nuclear plants are also significantly affected. A no learning situation would leave these two technologies in competitive disadvantage and with a marginal market share. When progress ratio is 1.0, the advanced coal plant is still a competitive alternative to conventional coal plants in a BaU situation, but its penetration is lower[17]. Under the stabilisation scenario, coal is phased out and advanced coal penetrates less than in the BaU case, but also here the difference is evident. Without learning the technology plays only a marginal role. The new nuclear technology is not competitive under the BaU scenario and will reduce its growth drastically in the stabilisation one if no learning is allowed.

As expected, the results of the model with endogenous technological learning are sensitive to the learning rates being assumed. Not attractive enough values of the progress ratio may imply the technology being "locked-out" of the system. The specific effects, however, seem to be case and technology dependent. As noted by Seebregts et al. (1998), non-competitive, marginally used, technologies are more sensitive to progress ratio (and other) assumptions. The sensitivity analyses are useful to study which would be the "break-even" progress ratio for a particular technology, that is the progress ratio which will make the technology competitive (although, of course, other factors will intervene in its penetration).

[17] There seems to be some evidence that advanced clean coal cycles may experience significant cost reductions in the future (Schrattenholzer, 1998). This, together with the reduced environmental impacts, could make them very interesting for those countries, which, due to resource constraints, will still have to rely heavily on coal to meet fast growing electricity consumption.

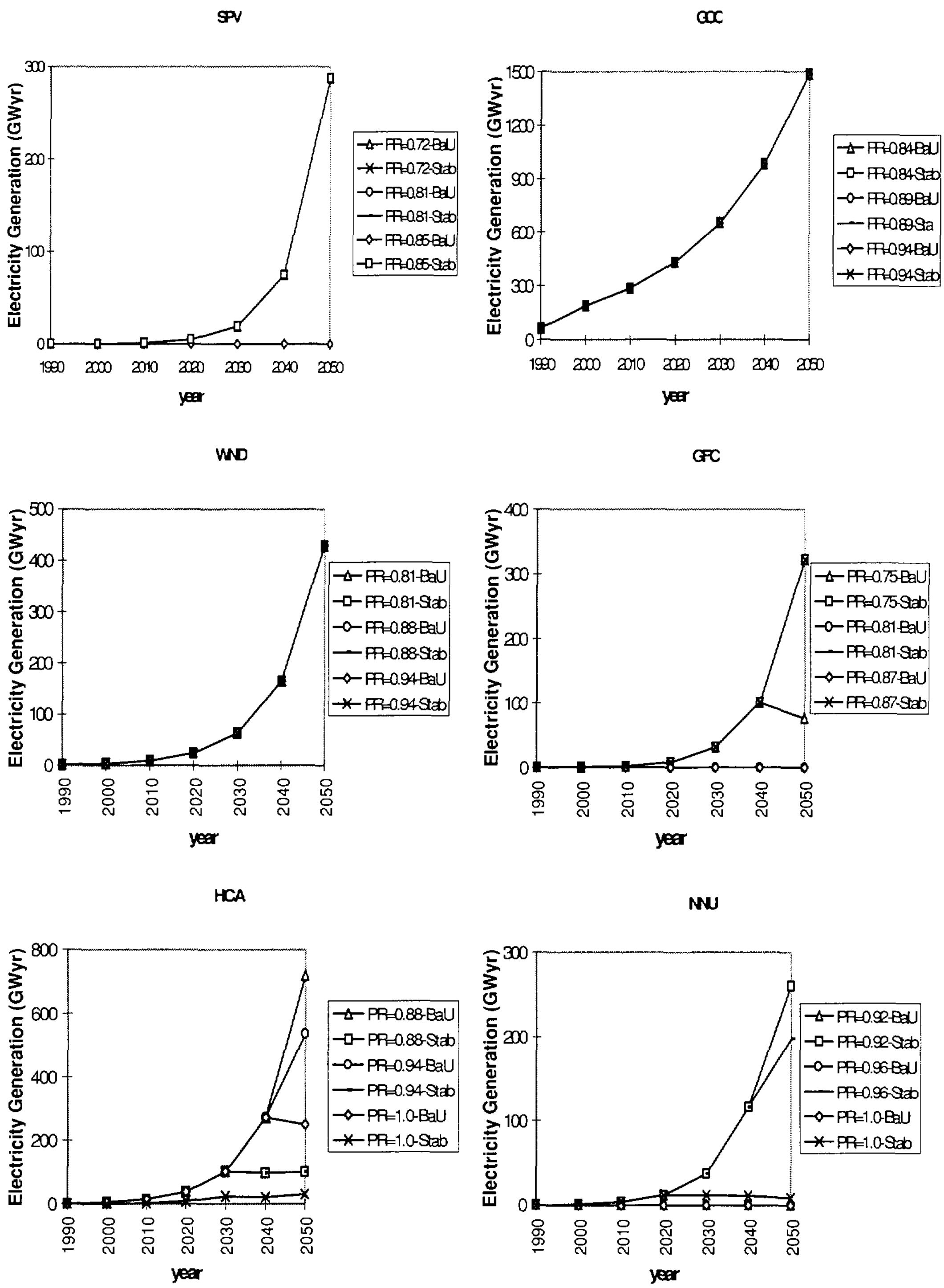

Figure 23. *Sensitivity to the progress ratio*

The values of maximum growth constraints are very influential in the penetration of learning technologies. Thus, they determine to some extent whether or not a variation is observed when the progress ratio is changed, as they affect the possibilities for a technology to learn along the time horizon[18]. Figure 24 presents the variation of the electricity generation under the stabilisation scenario when the maximum growth rate of the solar PV is modified from 10% to 20% per year. It is evident the increasing (although possibly unrealistic) role played by solar photovoltaics if it is allowed to grow at higher rates. With a lower growth rate, the technology may not have the opportunity to accumulate enough capacity to become cost-effective (there is not sufficient learning potential on the time horizon) and it can be "locked-out" from the system (as occurs here when the growth rate is 10%). However, once a learning technology becomes competitive, the MIP-learning model may try to install it up to the maximum cumulative capacity.

This is an example of a typical “lock-in” effect, which has to be handled carefully in the model. The underlying increasing returns mechanism drives the model to exhibit a "lock-in" behaviour. A learning technology that has become competitive due to the early investments, will be installed more and more. Although this behaviour is not a problem in itself, as it helps to reflect the processes of technological "lock-in" of the real life, it also calls for a careful and consistent selection of growth constraints, maximum potentials and progress ratios for the learning technologies in the model.

The progress ratio assumption, together with the maximum cumulative capacity, will condition the ultimate specific cost that it is possible to reach. If this one is very low, and the penetration constraints of the system under analysis permit sufficiently high values of capacity to be installed, possibly unrealistic cost reductions may be the result, which will on their turn drive to a further installation of capacity. Therefore, both maximum growth constraints and progress ratios will control the learning possibilities of a given technology and it is important to ensure a consistent definition, paying attention to their combined effect in the trajectory of a certain technology. Maximum growth rate constraints are advisable in controlling the penetration (that is the learning over time) of the technology, but there is still a compromise for what could be considered a “reasonable” value for the progress ratio.

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[18] The maximum growth constraints are introduced in the model to mitigate the "bang-bang" behaviour typical of linear programming models and provide a more realistic penetration of the technologies. However, the growth rates are exogenously specified. There is interest in providing the models with endogenous mechanisms that allow to reproduce the typical patterns of the market penetration of the technologies (which, for many technologies, it has been empirically observed that follows a logistic curve, Grübler, 1991), instead of imposing them exogenously. Recent experiences reported by Grübler and Gritchevskii (1997) have shown that the combination of learning curves and persistent uncertainty, two basic mechanisms at the core of the technological change dynamics, drive to logistic-like penetration patterns and consistent diffusion times. This is, in fact, a very interesting result, as the model is able to generate such patterns endogenously. It should be taken into account, for instance, for future developments in the ERIS model. For more detailed discussions see the above mentioned paper, Grübler (1998) or Grübler et al. (1999).

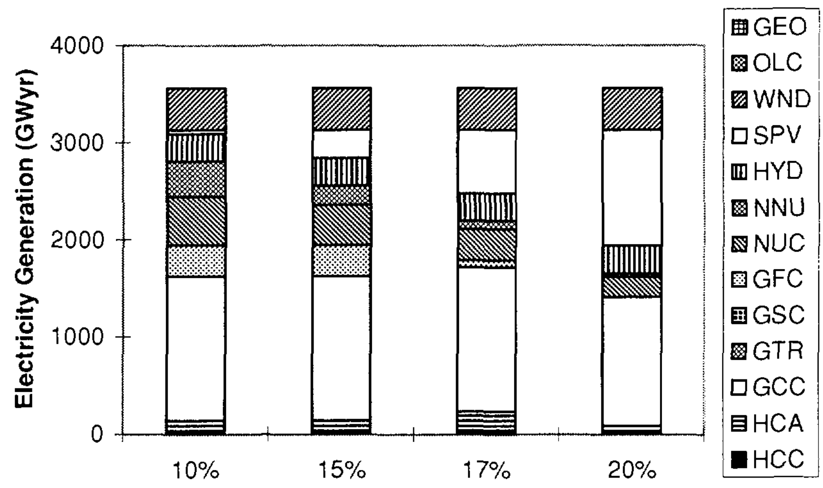

Figure 24. *Generation mix in 2050-Stabilisation scenario- Different growth rates for SPV*

4.3.3 Sensitivity to the discount rate

The discount rate used to compute the total system cost has a strong influence in the technology choice of the model (Messner, 1997). Here, its influence is examined for the MIP learning model. Figure 25 presents the comparison of the electricity generation for the BaU scenario in the year 2050 under three different discount rates (5,10,15%).

Several changes are noticeable when the discount rate is modified. If the discount rate is increased to 10%, the solar photovoltaics, a technology with high initial investment costs but relatively low O&M costs, that was competitive for the 5% discount rate case, is not introduced into the solution. On the other hand, the gas fuel cell, which did not appear previously, and has lower investment costs but much higher O&M costs, comes in. With a further increase to 15%, none of those technologies appear. In addition, when discount rate is increased, conventional coal plants and simple cycle turbines increase their output, while advanced coal plants and gas combined cycles decrease their production.

Under the stabilisation scenario, changes are less dramatic for the learning technologies, as low carbon technologies are forced into the solution due to the CO_2 constraint. However, also in this case, the model increases the generation of simple cycle gas turbines, at expense of the combined cycle gas turbine. Thus, as stated by Messner (1997), a higher discount rate favours technologies with lower up front investment costs, even if the operating costs are higher. As a consequence, emerging revolutionary technologies whose investment costs are still high, may not be chosen under a high discount rate. The corresponding effects of the discount rate variation on the emission profiles for the BaU scenario may be appreciated inFigure 27.

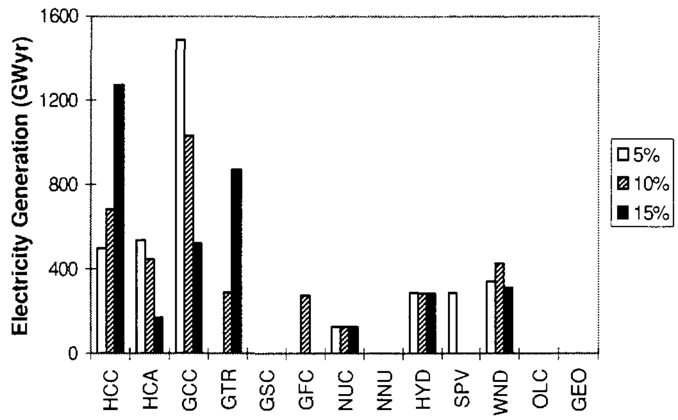

Figure 25. *Electricity generation mix in 2050. BaU scenario. Different discount rates*

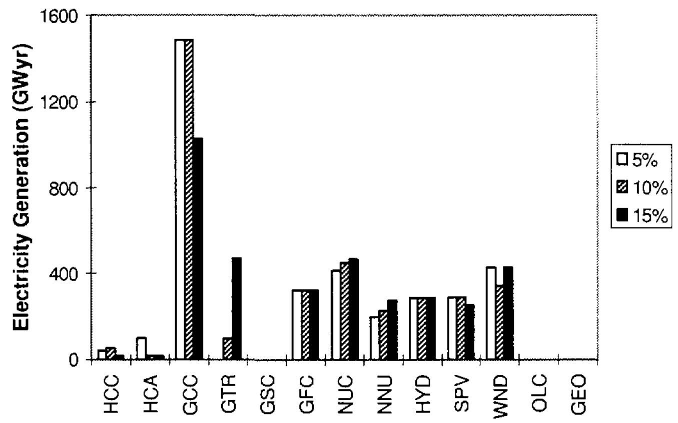

Figure 26. *Electricity generation mix in 2050. Stabilisation scenario. Different discount rates.*

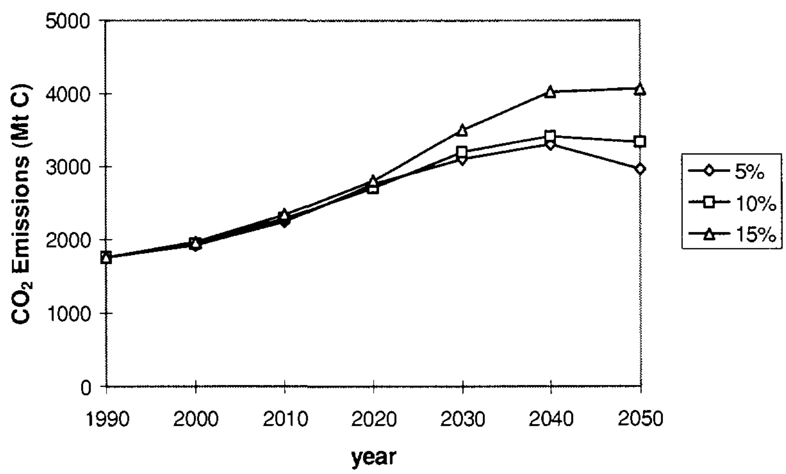

Figure 27. *CO_2 emissions from the global electric system. BaU scenario. MIP-Learning. Different discount rates*

4.3.4 Learning curves with several progress ratios

Another issue has to do with the fact that a certain technology may present different learning speeds along different stages of its life cycle. This is a phenomenon already observed for the gas turbines which had a faster learning in the R&D and demonstration phase, but it slowed down once the technology went to the competitive phase (Nakicenovic, 1997). Therefore, one could specify several progress ratios for different ranges of cumulative capacity. Using this approach the change of learning rates can be handled. However, a threshold capacity (C_{thres}), from which the learning speed increases or decreases has to be defined and the difficulty remains how to establish such a value. Here, a test of this procedure using arbitrary values has been done.

The test is done for the solar PV technology, for which the evolution with two progress ratios is considered. For this exercise, an arbitrary threshold value of 100 GW has been used. Figure 28 presents a comparison between the cumulative costs curves with different progress ratios and the two-stage learning curve. With the introduction of a new learning rate, the segmentation of the whole curve is altered because the maximum cumulative capacity associated with the first progress ratio is not anymore the absolute maximum cumulative capacity $C_{k,max}$, but the threshold capacity C_{thres}. For the second progress ratio, C_{thres} is now the initial cumulative capacity. In this case, 8 segments have been specified for the whole curve. Five segments for the first part of the curve and three for the second one. For each part, the variable length segmentation rule described in numeral 3.5 has been applied. Of course, alternative segmentation procedures for a two-stage learning curves may be defined.

Notice that in this example, with the original curve (pr=0.81) and the parameters used in this analysis, the investment cost for the gas fuel cell technology may go down to 350 US$/kW. The combination of two progress ratios provides a minimum specific cost of 970 US$/kW.

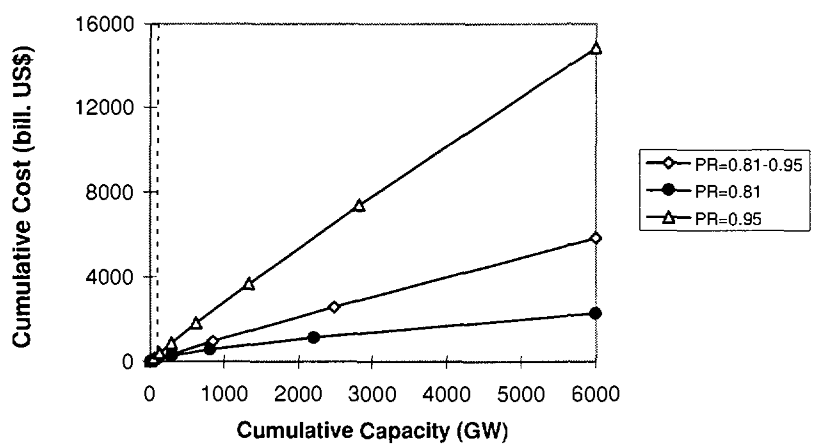

Figure 28. *The two-rates cumulative cost curve for solar PV*

Figure 29 presents the comparison of the electricity generation mix obtained with one single progress ratio (results presented above) and two progress ratios for the BaU scenario (results for the stabilisation scenario were not affected by this change). In the two-stage learning case, the solar PV technology is not cost competitive for the reference conditions, and, consequently, the generation with advanced coal plants and wind turbines is higher than in the one-stage case.

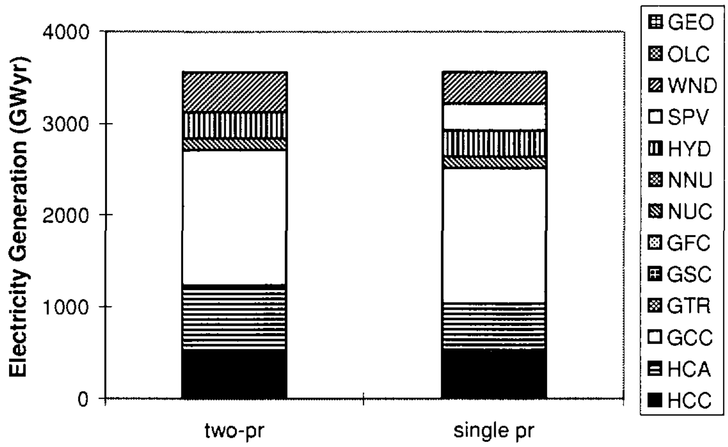

Figure 29. *Comparison of generation mix in 2050 - One Vs Two progress ratio- BaU scenario*

It could be useful to use several progress ratios when unrealistic cost reductions have to be avoided. The cost reduction could be controlled using a two-stage learning model. Messner (1997) imposed a lower bound for the specific cost of the learning technologies while Mattsson (1997) decided to let the natural saturation of the learning curve to control the cost reduction without imposing any lower bounds, as is done in our previous runs reported above. However, under the particular conditions of our analysis, with the progress ratio values been used up to now, some of the technologies may go to fairly low investment costs. A two-stage learning model may be useful in specifying realistic limits of the cost reduction, without imposing a fixed lower bound that rules out the possibility of further learning for a particular technology.

It is interesting to analyse which learning conditions will allow or prevent the entrance of a specific technology into the marketplace and which may be the effects of speeding up/slowing down the learning process at further stages of evolution of a certain technology. Will the model still find a given technology attractive despite future changes of the learning process?. In this respect, analysis with Learning-MARKAL may give support to other policy studies in the identification of specific actions to promote the deployment and diffusion of new, innovative technologies, which will enable the transition to more environmentally compatible energy systems.

5. A post-Kyoto analysis with the ERIS model prototype

Here, using a multi-regional version of the ERIS model prototype incorporating endogenous technological learning, a simplified analysis of the global electricity generation system has been performed. The results presented here are drawn mainly from Barreto and Kypreos (1999). The main purpose of this analysis is to provide a general picture of the long term evolution of the global generation mix, examining the possible effects of Kyoto-like CO_2 constraints when technological learning is present. In addition, using a two-stage programming approach, some stochastic analyses are performed to examine the effect of uncertainties in the CO_2 reduction targets, demand and learning rates. Also, a preliminary analysis of the effects of the geographical scale of learning is included.

The same technological parameters and learning curves described in numeral 4.1 are used. A generic specification of generation technologies has been introduced across the different regions. That is, besides installed capacities, availability factors and potentials for renewable technologies, no regional specification of costs or technical characteristics is carried out. However, for solar PV and gas fuel cell, an explicit "floor" specific investment cost of US$ 500/kW is provided. This represents a "cutting-off" on the learning process, which could be arguable from a conceptual point of view, but it is incorporated in order to avoid unrealistic cost reductions.

5.1 Regionalisation

For this analysis, the regionalisation of ERIS has been chosen following that of the MERGE3 Model (Manne and Richards, 1997). That is, nine geopolitical world regions have been considered. Four regions represent the industrialised countries: United States (USA), Western Europe (OECDE), Canada, Australia and New Zealand (CANZ) and Japan (JAPAN). One region represents the economies-in-transition: Eastern Europe&Former Soviet Union (EEFSU). Together, the five regions conform the Annex I group. Four additional regions group together the developing countries: China (CHINA), India (INDIA), Mexico and OPEC (MOPEC) and the Rest of the World (ROW). This regionalisation suffices for the purposes of our generalised analysis, but more detailed studies could require a different definition of the regions according to different criteria (e.g. similarities in their electricity markets, geographical, etc.). In this indicative analysis, no attempt was made to conceive a new regionalisation and the results will be presented mainly at an aggregated global level.

5.2 Electricity demand

The demand corresponds to the REFXII/A2 scenario resulting from the combination of the REFXII scenario from the POLES model (Criqui, 1999) and the A2 scenario from IIASA-WEC (1998). It is therefore a high growth scenario and should not be regarded as a "reference" scenario in the usual sense[19] . In this projection, global electricity demand

[19] Future developments with the ERIS prototype contemplate linking it to the MERGE3 model. Scenarios

grows at an average of almost 3% per year between 2000 and 2050. Annex I countries account for 43% of the world-wide electricity demand by the year 2050. Figure 30 presents the regional demands and Figure 31 provides a comparison of the aggregated global demand with that of the IIASA-WEC A2 scenario.

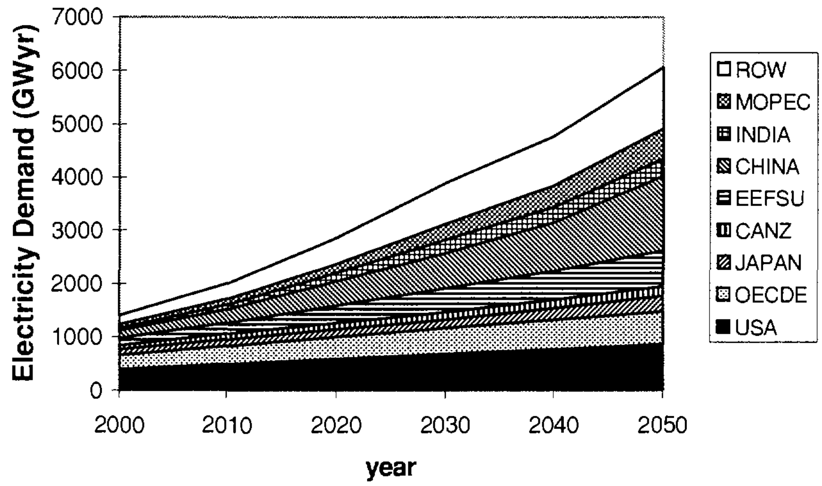

Figure 30. *REFXII/A2 electricity demand scenario*

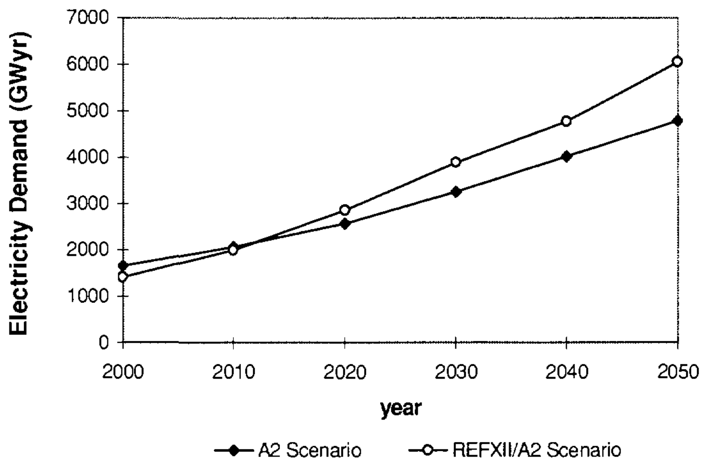

Figure 31. *Comparison between TEEM REFXII/A2 and IIASA-WEC A2 scenarios*

5.3 Definition of CO_2 emission scenarios

Regarding CO_2 emissions three basic scenarios have been considered. The first one examines an unconstrained situation (Business as Usual, BaU). The second one imposes a constraint on CO_2 emissions on the Annex I regions, assuming that their electricity systems

could also be generated using such approach are compelled to achieve the Kyoto-agreed percentage reduction from the 1990 levels by the year 2010 and keep these levels constant for the rest of the horizon (Kyoto-for-ever).

For the fulfilment of the Kyoto-for-ever target, three different variants have been considered. In the first one, the emission targets must be fulfilled in each Annex I region, that is no trade of emission permits is allowed. In the second one, trade is allowed among the Annex I regions. In the third variant the influence of allowing emissions trade across all regions is examined, extending the trade to non Annex I regions after the year 2030. In order to avoid carbon leakage, in the constrained scenarios non Annex I regions are bounded to their BaU baseline emissions.

As a complement, an additional CO_2 constrained scenario is analysed where both Annex I and non-Annex I regions face emission reduction commitments (Kyoto global trend scenario). In this scenario Annex I countries follow a "Kyoto trend" constraint, with a linear extrapolation from the target for the year 2010 (5% per decade until 2050). The non-Annex I countries face an arbitrary linearly decreasing CO_2 target imposed for the period 2030-2050 (5% per decade after 2030). Trade across all regions is allowed after 2030.

It should be noticed here that, although the attention has been concentrated in CO_2 emissions, other pollutants such as SO_2 or NO_X , related to regional and local pollution problems, will also play an important role in the selection of generation options around the world [20].

5.4. Some results

5.4.1 Unconstrained scenario (BaU)

Figure 32 presents the evolution of the global generation mix for the CO_2 unconstrained (BaU) scenario, under the above described assumptions. A clear dominance of coal plants is evident in the satisfaction of the rapidly increasing demand. Although mainly conventional units are installed, advanced coal power plants are also introduced. However, gas combined cycle plants experience a very significant growth becoming the dominant technology by the end of the horizon. Oil-fired generation is practically phased out and nuclear keeps a small share. Wind turbines, already an economic alternative in several markets, are introduced along their maximum penetration constraint. Gas fuel cells also undergo a certain growth, though their participation remains modest. Under these circumstances, solar photo-voltaics is not economic and is not introduced.

Figure 33 presents the regionalised evolution of CO_2 emissions from electricity generation in this scenario. A substantial increase occurs along the time horizon. Developing regions, with fast growing electricity markets relying upon indigenous fossil fuel resources (mainly

[20] The model database can be extended to introduce information concerning specific emissions of regional pollutants and corresponding control technologies. The effects of regional pollution control policies on the generation mix may be examined, and synergies and/or conflicts with CO_2 policies assessed.

coal) to meet the demand, become important contributors to the global CO_2 emissions in the long term.

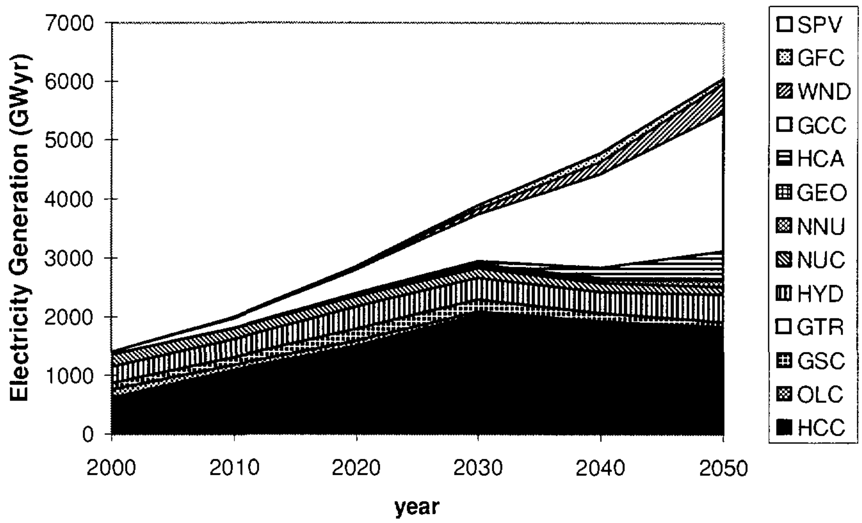

Figure 32. *Global electricity generation. BaU scenario.*

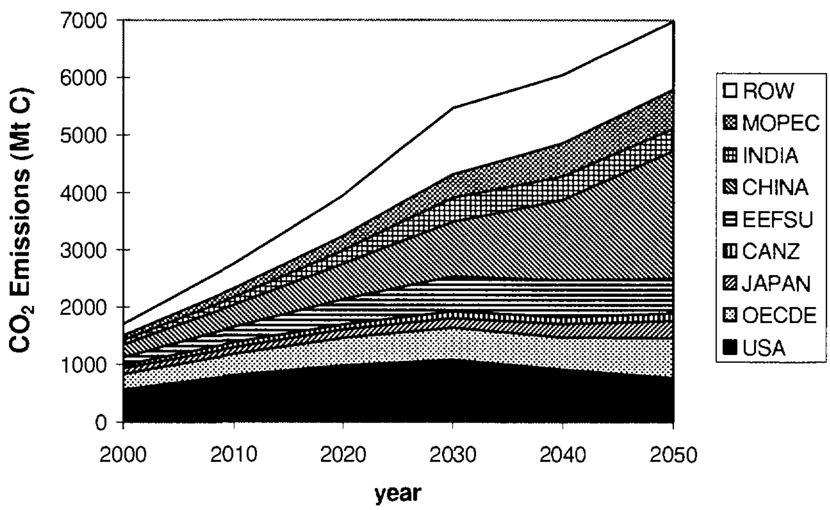

Figure 33. *CO_2 emissions from the global electricity system. BaU scenario*

5.4.2 Kyoto-for-ever scenario

In this section the behaviour of the system under the Kyoto-for-ever target is examined under different assumptions concerning trade of emission permits.

5.4.2.1 No trade

In first place, the fulfillment of the Kyoto-for-ever target without allowing trade among the regions is examined. Figure 34 presents the electricity generation mix and the corresponding CO_2 emissions are presented in Figure 35.

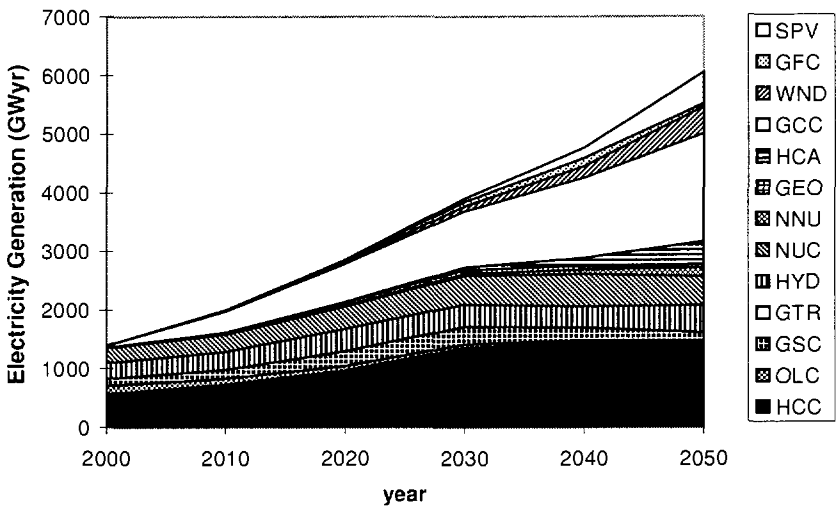

Figure 34. *Global electricity generation. Kyoto-for-ever scenario. No trade*

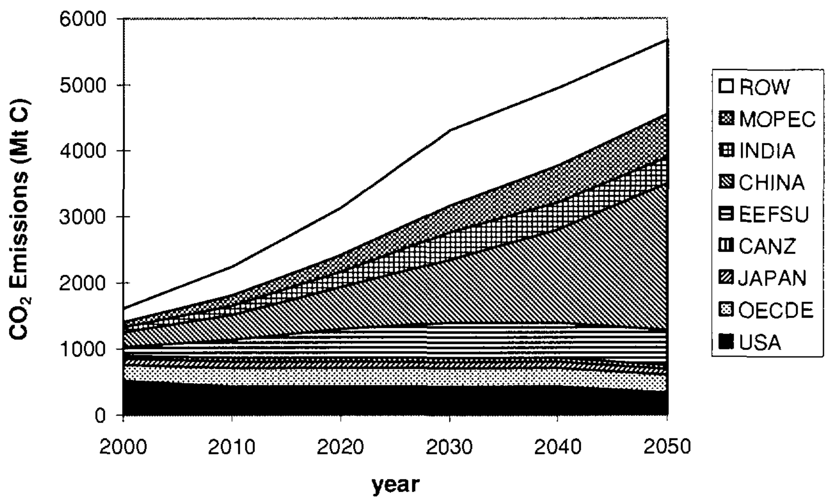

Figure 35. *CO_2 emissions per region. Kyoto-for-ever scenario. No trade*

The constraints imposed in the Kyoto-for-ever scenario provide an opportunity for the introduction of less carbon-intensive or carbon-free technologies in the regions with reduction commitments. This situation implies a significant departure from the coal intensive trajectory the system was following in the previous unconstrained scenario (see Figure 34). Coal, however, still continues to be an important primary fuel in the electricity supply, through both conventional and clean coal technologies. In particular, some of the non-constrained regions continue to rely heavily on it (CHINA and INDIA). Nuclear (both conventional and new) plants experience a significant growth. Gas fuel cell is introduced to a minor extent, lower than in the BaU case. Despite the fact that Annex I countries achieve long-term stabilization of their CO_2 emissions, global emissions still experience a substantial increase.

Under this scenario, Solar PV becomes an attractive technology penetrating to a large extent in Annex I regions but also, though to a smaller extent, in non Annex I regions (see Figure 43 and Figure 44 below for a comparison of the generation mix for the year 2050, in Annex I and non Annex I groups, for the three trade variants considered). In this situation, the technological learning stimulated by the constraint is sufficient to bring the costs of Solar PV to competitive levels. It is important here to notice how the representation of endogenous learning influences the outcome. As global spill-over for learning has been assumed, cumulative capacities are added up across all regions in order to compute the resulting investment costs for the learning technologies. Therefore, installation of a certain technology in one region will affect the uniquely defined investment cost and can certainly make this technology economic in another region. A simple sensitivity to the geographical scale of learning is presented in the section 5.6.

5.4.2.2 Trade among Annex I regions

In this case, trade is allowed among the Annex I regions. The possibility of trading emission credits allows some Annex I regions to follow more moderate changes in the structure of their electricity generation systems. However, while output from gas combined cycle plants increases, generation from conventional coal plants remains low, well under the BaU levels. The generation mix of the non Annex I group remains essentially unaltered, with the exception of solar PV which reduces its share in both Annex I and Non Annex I countries when compared to the no trade situation. Here, the global spill-over in learning also plays a role. As lower investments on solar PV are carried out in the Annex I group, smaller cost reductions are experience and therefore, lower installations also occur in the non Annex I group. Besides the significant change in solar PV, the situation at the aggregated global level is not markedly different from that in the case without trade (see Figure 43 below).

As the emissions target for the EEFSU region exceeds by far the level of emissions, the EEFSU becomes the main seller of emission credits along the horizon. That is, the so-called "carbon bubble" created in the Former East Block due to the economic crisis, exerts a significant influence on the trade[21] and, therefore, in the fulfillment of the Kyoto-for-ever target. In fact, in this situation global emissions are slightly above than in the previous no trade variant.

5.4.2.3. Full trade

When emissions trade across all regions is allowed, a fraction of the abatement effort occur in some of the non-Annex I regions where gas CC and conventional coal plants output is reduced, while less carbon intensive options increment their production levels. In

[21] For a comprehensive analysis of the possible effects of the "carbon bubble" on the compliance of the Kyoto Protocol see, for instance, Victor et al. (1998). According to their analysis, Russia and Ukraine would be very likely the major contributors to sales of "bubble" permits.

particular, a much higher penetration of solar PV than in the previously examined variants of the Kyoto-for-ever scenario is observed. The Annex I regions undertake a less radical decarbonisation in their generation mix, as they are allowed to fulfill part of their commitments by means of international cooperation mechanisms. In particular, less generation from nuclear, solar PV and hydro is observed in this group of countries, while coal and gas power plants increase their output. Gas fuel cells are introduced to a higher extent than in the previous cases, but they do not grow enough to gain a sizable share of the market.

The comparison of the generation mix, for the year 2050, in Annex I and non-Annex I countries, under the Kyoto-for -ever constraint for the no trade, trade in Annex I countries and full trade situations is presented inFigure 36 and Figure 37.

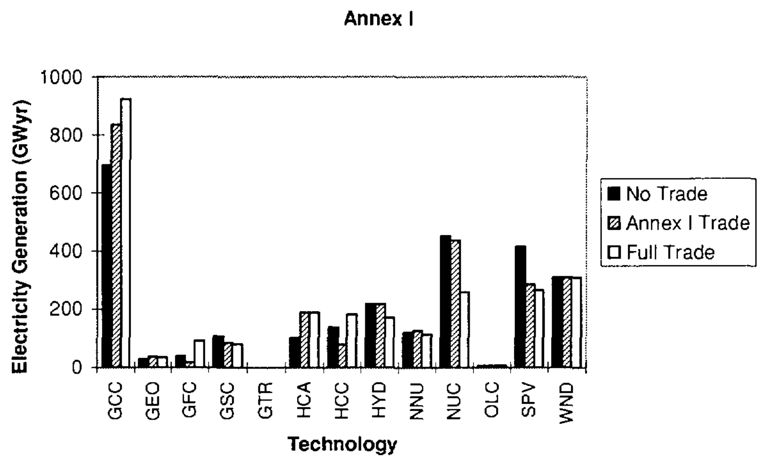

Figure 36. *Electricity generation in the Annex I group in 2050. Kyoto-for-ever scenario*

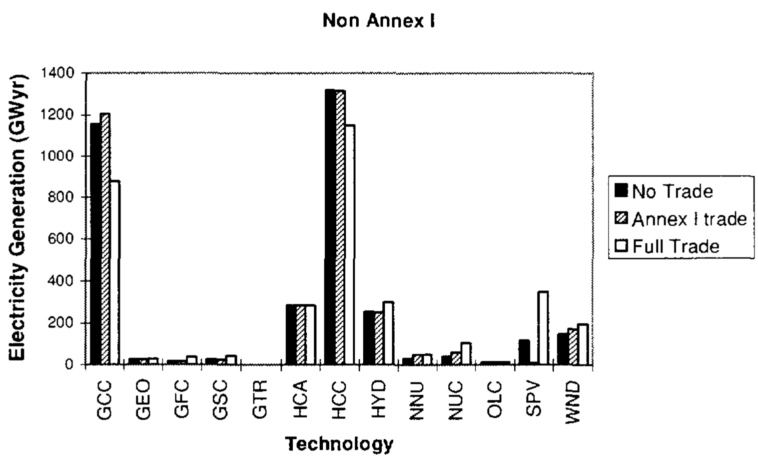

Figure 37. *Electricity generation in the Non Annex I group in 2050. Kyoto-for-ever scenario*

It has to be mentioned that the possibility of trading emission permits, either within Annex I regions or together with non Annex I countries, does not imply that abatement measures are not undertaken inside the regions facing CO_2 mitigation commitments. Even more, when technological learning is endogenous, trade of emission permits may provide opportunities for introduction of learning technologies in different regions.

Figure 38 presents the CO_2 abatement costs for the different variants of the Kyoto-for-ever scenario. Abatement costs are defined here as the difference in total cumulative discounted system costs to the BaU scenario. For comparison, the abatement costs obtained for the same target and trade variant when technology costs are considered time-independent (Linear Programming static model) are also presented in the same figure. The benefits of trade and technological learning can be appreciated.

The results of the model under the Kyoto-for-ever scenario show that, when technology dynamics is endogenised, mitigation policies play an important role in inducing the technological development of clean technologies. Although the results presented here cannot be considered, by no means, exhaustive, this behaviour would indeed be in line with the claim that early action is required to induce and stimulate the necessary technological learning (Grubb, 1997, Grübler and Messner, 1998, Nakicenovic, 1997).

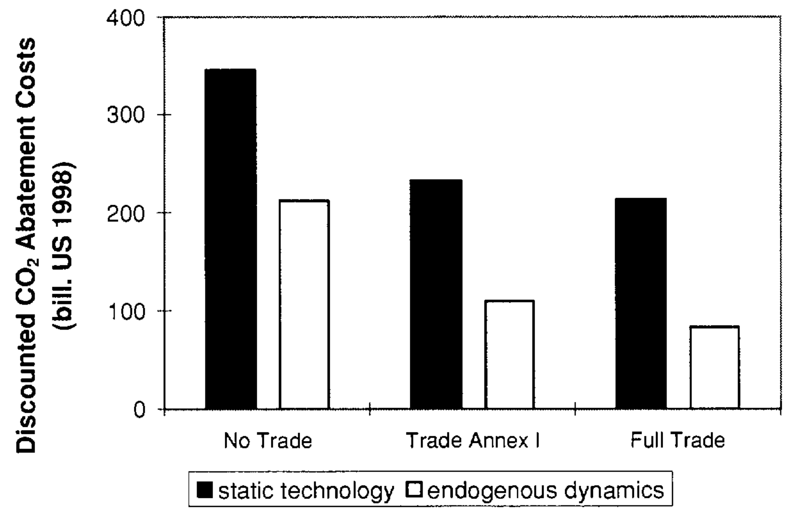

Figure 38. *Comparison of discounted CO_2 abatement costs. Kyoto-for-ever scenario*

5.4.3 Kyoto global trend scenario

Here, the results for this scenario, where both Annex I and non-Annex I countries face CO_2 reduction targets and trade across all regions is allowed, are presented. It represents a more stringent reduction than the previous cases, as the non Annex I countries, that did not face any restriction in the previous scenarios (besides, of course, the bounds to avoid carbon leakage), must commit themselves to abatement actions.

The time evolution of the global electricity generation for this scenario is presented in Figure 39 and the corresponding regionalised CO_2 emissions in Figure 40. Under this stronger reduction commitment, conventional coal power plants begin to be phased out after 2030 and advanced coal plants experience a much lower penetration than observed in the other situations. Higher amounts of solar photovoltaics and gas fuel cells (this one barely used in the Kyoto-for-ever case) are introduced to the system. Also, conventional nuclear production is increased. Gas combined cycles and hydro plants experience no significant variation in comparison to the previous cases.

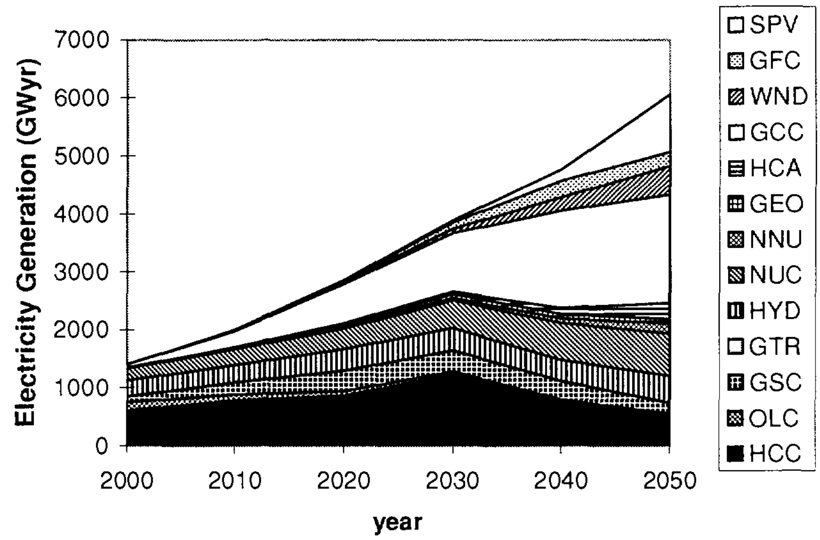

Figure 39. *Electricity generation. Kyoto global trend scenario*

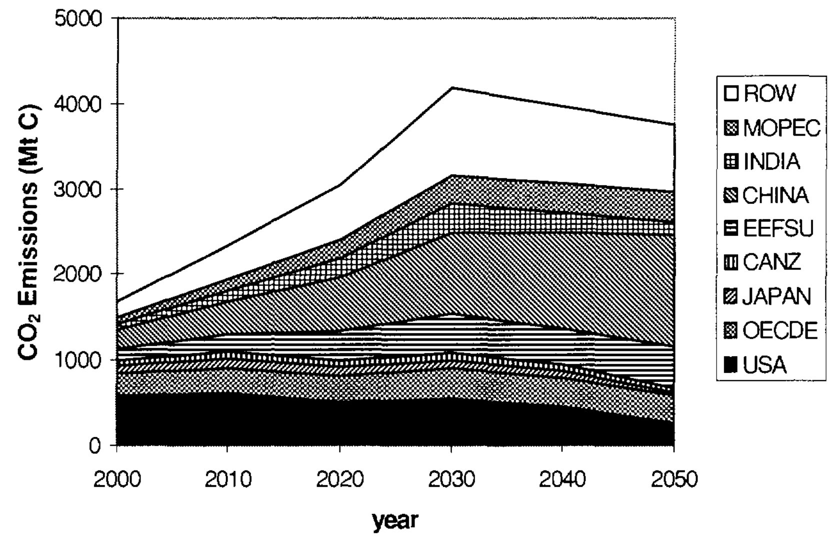

Figure 40. *CO_2 emissions from the global electricity system. Kyoto global trend scenario*

Figure 41 and Figure 42 present a comparison of the electricity generation per technology in Annex I and non-Annex I countries, for the year 2050, under three different CO_2 scenarios. Important structural changes of the generation mix are noticeable as the emission constraints become more stringent. Several emerging technologies, such as solar photovoltaics, wind turbines and gas fuel cells experience a very significant growth in both the developing and developed countries. Nonetheless, the gas combined cycle plant continues to be the dominant technology in both groups. Conventional coal generation is significantly reduced, and the bulk of the remaining coal electricity production in this scenario is carried out in the developing countries.

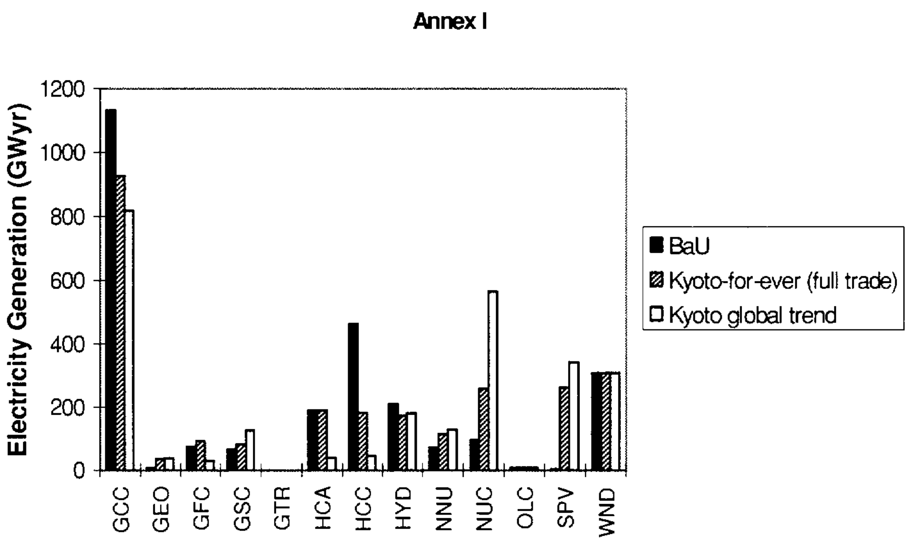

Figure 41. *Comparison of electricity generation mix in 2050. Annex I group. BaU, Kyoto-for-ever(full trade) and Kyoto global trend scenarios*

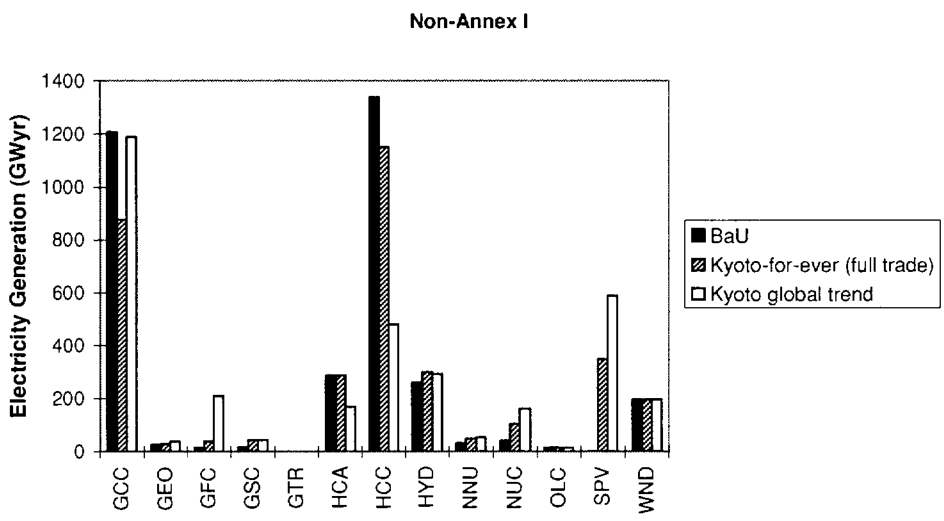

Figure 42. *Electricity generation mix in 2050. Annex I group. BaU, Kyoto-for-ever (full trade) and Kyoto global trend scenarios*

As a comparison, Figure 43 depicts of the global electricity generation mix in the year 2050 for the different scenarios and cases. Figure 44 presents the comparison of the regional CO_2 emissions for the same year and cases and Figure 45 the global evolution of emissions along the time horizon. Among the Kyoto-for-ever constrained cases, the trade in Annex I variant exhibits the higher global emissions. Emissions in the Kyoto global trend scenario are significantly lower than those in BaU as this constraint demands important abatement actions from developed and developing countries alike. In particular, for some developing regions such as CHINA, this commitment implies a strong reduction.

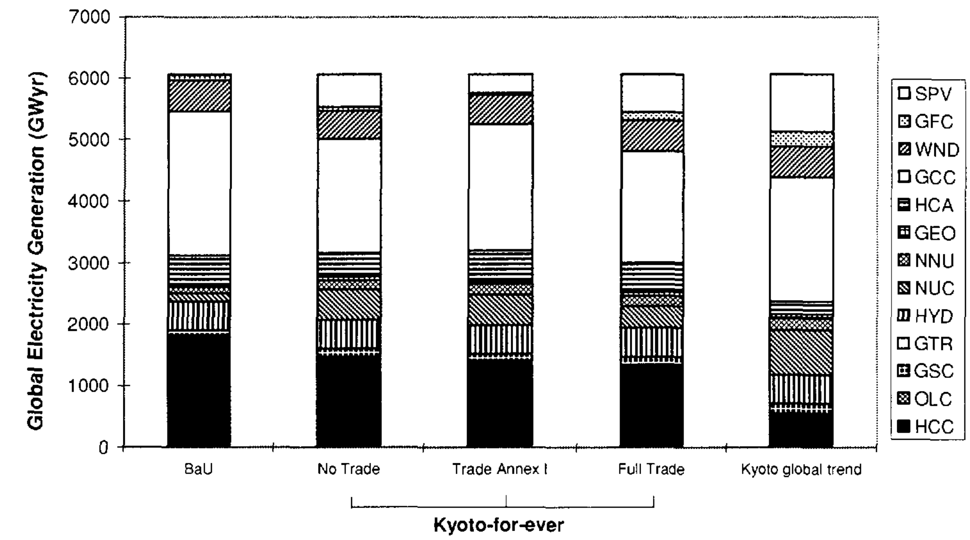

Figure 43. *Global electricity mix in 2050. BaU, Kyoto-for-ever and Kyoto global trend scenarios*

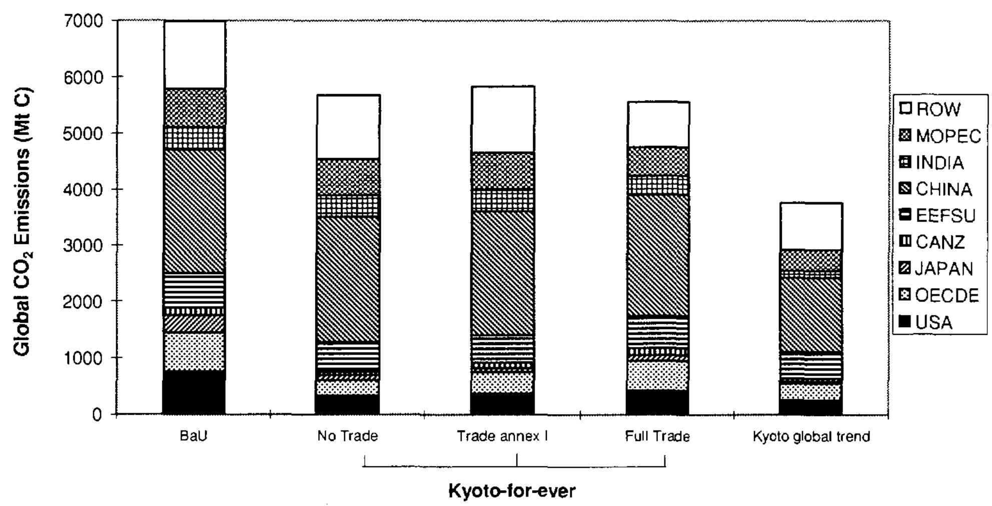

Figure 44. *Regionalised CO_2 emissions in 2050. BaU, Kyoto-for-ever and Kyoto global trend scenarios*

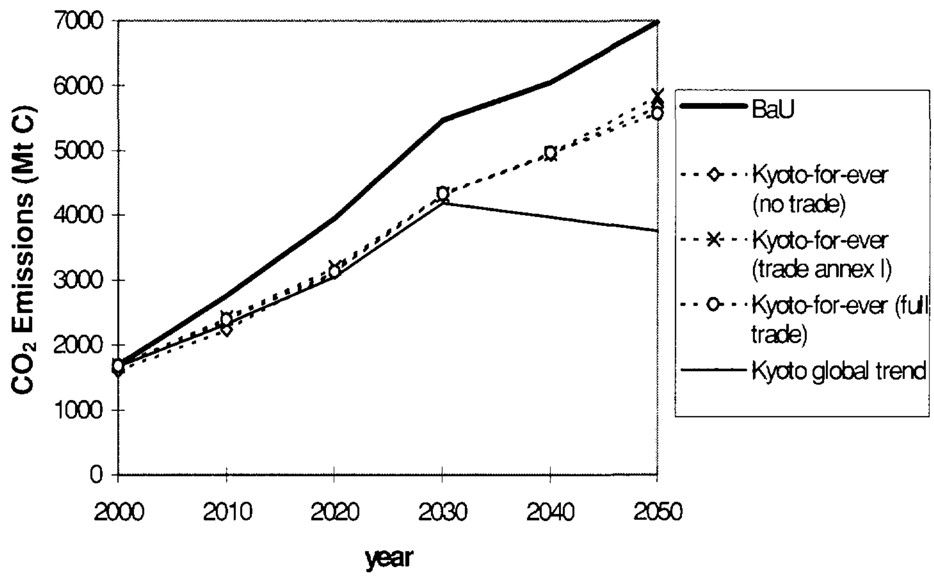

Figure 45. *Comparison of global CO_2 emission trajectories. BaU, Kyoto-for-ever and Kyoto global trend scenarios*

5.5 Stochastic analyses

Some stochastic analyses have been performed to examine the influence of uncertainty in CO_2 constraints, demand growth and learning rates in the evolution of the system. In each analysis only one of these parameters is considered uncertain and uncertainty is assumed to be resolved in time (in the year 2030) for all of them. As a simplifying assumption, all states of the world are considered with equal probability of occurrence.

5.5.1 Stochastic CO_2 constraint

For the analysis of uncertainty on the mitigation targets the system may face, two states of the world are considered: unconstrained CO_2 emissions and Kyoto-for-ever (without trade) commitments. Figure 46 presents the evolution of the global carbon intensity for electricity generation (ton C/kWyr) as an outcome of the stochastic analysis and compared to the previously described deterministic cases. In the stochastic situation, during the first stage the electricity generation system basically follows the same decarbonisation path of the deterministic Kyoto-for-ever target. Capacity is built up in low-carbon or carbon-free technologies (mainly solar PV and conventional nuclear, but also, but to a lower extent new nuclear and gas fuel cells). Figure 47 presents a comparison of the corresponding generation mix obtained for the year 2050.

The early investments induced by the first stage emission reduction results in cost reduction and market penetration of several emerging learning technologies. This drives to a much lower carbon intensity, as compared to the deterministic BaU trajectory, even in the unconstrained state of nature (BaU-Sto), which is progressively less affected in the second stage. As illustrated with these results, uncertainty in emission reduction commitments drives to early action as a preparation for future contingencies. When technological learning is endogenous, the investments induced by this hedging policy will contribute to the required technological progress, possibly making more intense mitigation actions in the long term less expensive.

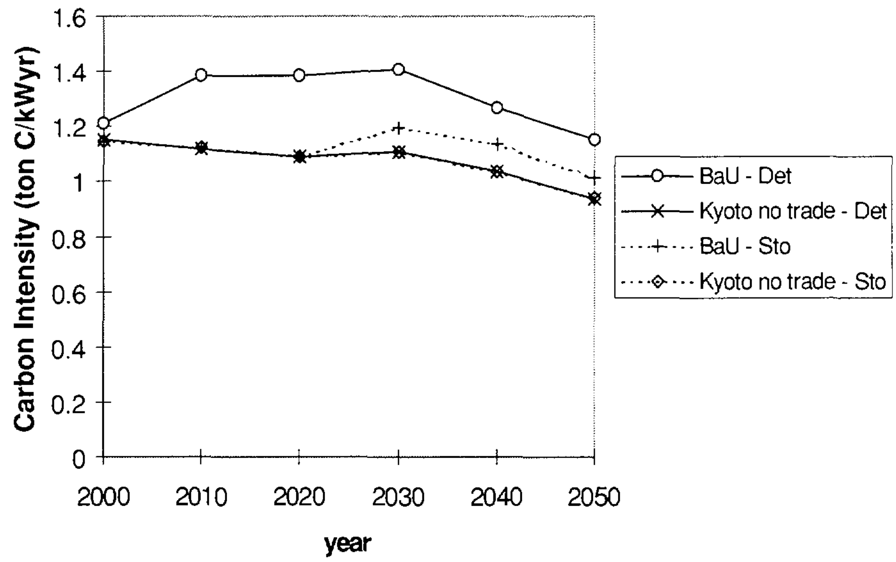

Figure 46. *Carbon intensity of global electricity generation. Stochastic analysis*

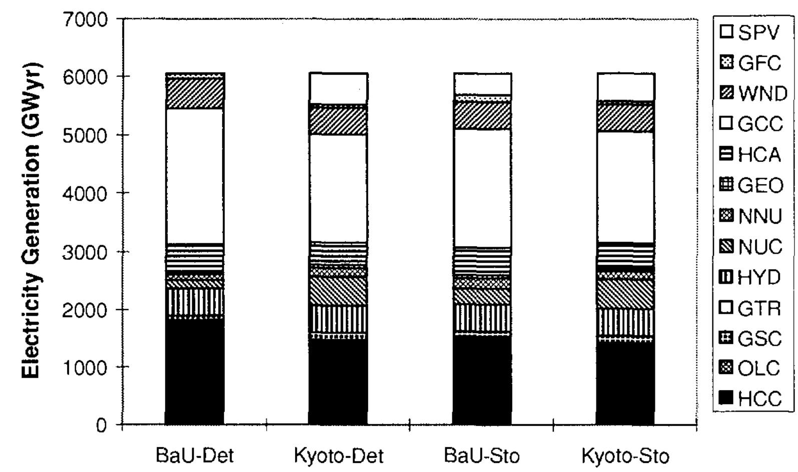

Figure 47. *Comparison of generation mix in 2050. Stochastic Vs deterministic cases*

5.5.2 Stochastic demand growth

Future trends of the demand are highly uncertain and will affect the technology choice, resource consumption and resulting emissions in the global electricity system. In order to examine the impact of uncertain demand growth rates, two states of the world are considered here. The first one considers the electricity demand examined so far, and a second state is specified with a lower demand (-15% from 2010). Figure 48 presents, for the year 2020, the electricity generation for five of the six learning technologies (GCC is excluded because it is not an emerging technology and the magnitude of its generation does not fit into the scale for comparison) in the stochastic case as compared to the corresponding deterministic high and low demand scenarios for the Kyoto-for-ever CO_2 constraint (no trade). The possibility of a higher demand may provide opportunities for higher growth in some technologies, favoring early learning. This is reflected in the stochastic case, where solar photovoltaics and gas fuel cell experience a higher growth than they do in the low demand deterministic case. The early investments of the first stage in low carbon and more efficient technologies, stimulated by a possible higher demand, result in a different (lower) emission trajectory in the second stage for the low demand state-of-the world (see Figure 49).

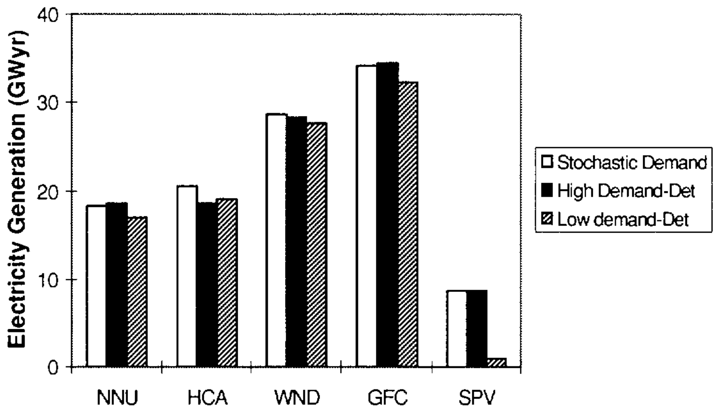

Figure 48. *Electricity generation from learning technologies in 2020. Stochastic Vs deterministic demand. Kyoto for ever scenario (no trade)*

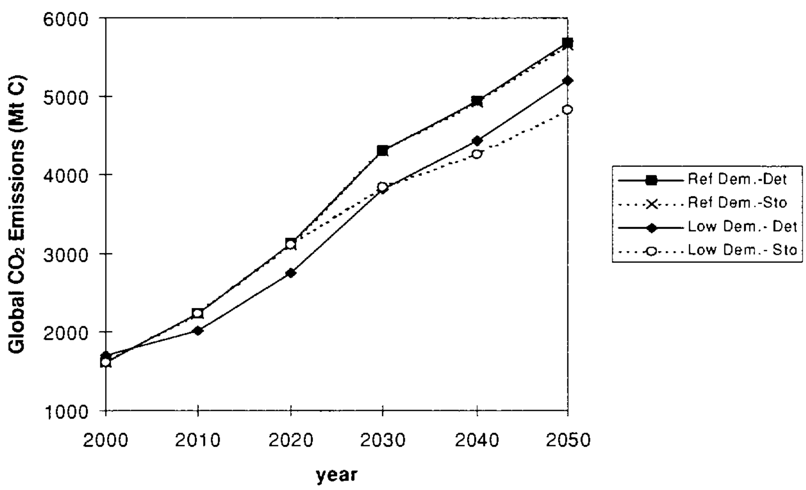

Figure 49. *Comparison of global emissions for the Kyoto for ever scenario (no trade). Stochastic Vs deterministic demand*

5.5.3. Stochastic progress ratio

The progress ratio constitutes one of the fundamental and most sensitive assumptions when technological learning is endogenised. However, there is significant uncertainty regarding the future values this parameter may exhibit and even historical estimates provide different values depending on data sets, time span and performance indicators used (Schrattenholzer, 1998, Neij, 1999).

A number of not easily predictable factors intervene in the learning or "forgetting" processes that will drive to the progress or stagnation of a given technology. It is possible that a slowdown or a further acceleration of learning occur as the technology proceeds from its infancy to its maturity (Ayres and Mártinas, 1992, Grübler et al., 1999). However, further research is required to establish which factors may affect the progress ratio and whether it varies significantly in different stages of the life cycle for a given technology.

Here, the influence of progress ratio is examined for the solar PV technology. Up to this point in this analysis, a progress ratio of 0.81 has been considered. Being an emerging technology, solar PV very likely has ample room for improvements. However, the potential for cost reduction is still uncertain.

Three states of the world are considered. Solar PV may assume either a PR=0.72, PR=0.81 or PR=0.90 22. The evolution of cumulative capacity over time is used to compare the stochastic outcome with the deterministic cases. Figure 50 presents the relative comparison for the cumulative capacity of solar PV under the Kyoto-for-ever scenario (full trade), between the deterministic and the stochastic cases. Cumulative installations for the deterministic case with PR=0.81 have been chosen as reference.

The deterministic case with PR=0.72, presents, as expected, a higher level of early investments. Obviously, if the technology were able to follow a steeper learning curve, competitive investment costs will be reached earlier. The deterministic case with PR=0.90 results in a much smaller growth of the technology. The progress ratio is not attractive enough to bring significant investments and the technology remains marginal. In the stochastic case, with uncertainty about the progress ratio present, the model tends to follow an intermediate hedging path in the first stage, driving to a more gradual diffusion of the technology than that observed for the PR=0.81 and PR=0.72 deterministic cases, but avoiding the "lock-out" of the technology occurring in the case PR=0.90. Thus, as possibilities for high learning exist, in the stochastic case the model gradually builds up a certain amount of capacity (that is, letting technological learning to take place), that will allow further growth and development of the technology in case it is required[23].

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[22] Although the progress ratio values are very different, the effect of this difference is somewhat reduced because the curves must converge to the same specific "floor" cost. This reduces to some extent the expected benefits of PR=0.72. The curve with PR=0.90, however, will always be well above the "floor" cost.

[23] The stochastic case increases the size of the model considerably (14352 constraints, 8932 variables) as compared to the deterministic one (5328 constraints, 3356 variables). The solution is much more difficult and solution times are, correspondingly, significantly higher (90 Vs 17 minutes in a Pentium PC 300 MHz

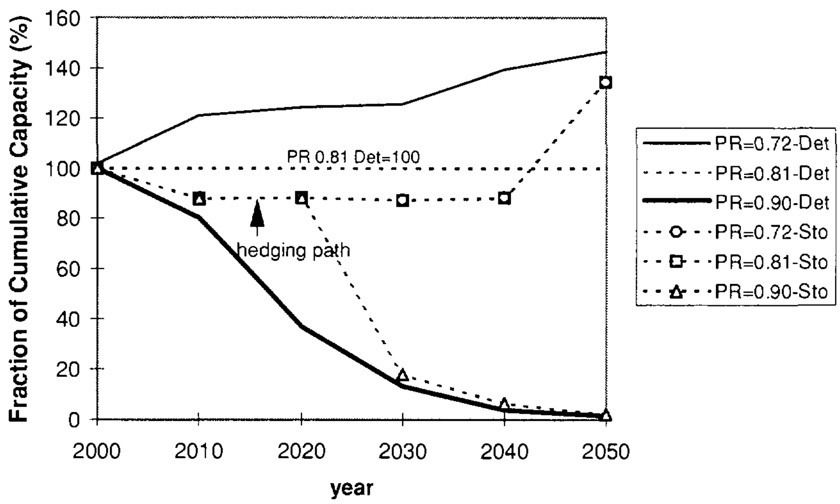

Figure 50. *Cumulative capacity relative to the deterministic PR=0.81 case. Kyoto for ever scenario (full trade). Stochastic Vs deterministic cases*

Previous stochastic analysis for uncertain learning rates have been carried out by Mattson (1998) and Grübler and Gritsevskii (1997). Those analyses, however, have followed different approaches than the traditional two-stage approach with uncertainty resolution occurring at a common fixed date applied here. Mattson (1998), instead of a given time period, uses a pre-specified cumulative capacity threshold to resolve the uncertainty, on the rationale that information about the learning rates is obtained only if actual investments take place. This alternative, drives to a multi-stage problem where uncertainty is resolved independently for each technology.

Grübler and Gritchevskii (1997) follow a more complex stochastic programming approach, which does not rely on the assumption that uncertainty is resolved at a certain point on time. Uncertainty is persistent along the time horizon and a probability distribution is specified for the learning rates. Using this probability distribution stochastic samples are drawn and integrated into an overall objective function. It would be interesting to explore further these alternatives and establish whether they can be implemented in ERIS.

5.6 Global Vs regional learning

As a first attempt to analyze the consequences of cooperative versus non cooperative learning, a sensitivity exercise has been carried out considering that the regions may learn separately (though it is assumed that they follow the same learning curve). That is, accumulation of experience in one region does not influence cost reductions on the other(s). Although such regional differentiation on the learning could be possible, the

for one of our typical cases).

dynamics of learning processes at international level are highly complex and the intervening regions can not be easily determined. Petersik (1997), for instance, reports that the computation of the capital cost reduction applied in the DOE/NEMS model for new electricity generation technologies in the USA, includes the capacity installed and operated in other regions of the world by firms competing in the USA.

Here, two arbitrarily chosen main learning groups have been considered: Annex I and Non-Annex I countries. The exercise should be regarded as an indicative speculation about the consequences of having global or regional learning. The impact of non-global learning is better appreciated for the situation where trade across all regions is allowed. Figure 51 and Figure 52 present the comparison of the generation mix for the Annex I and Non-annex I groups in 2050, for the Kyoto for ever scenario (full trade), when global and regional learning are considered.

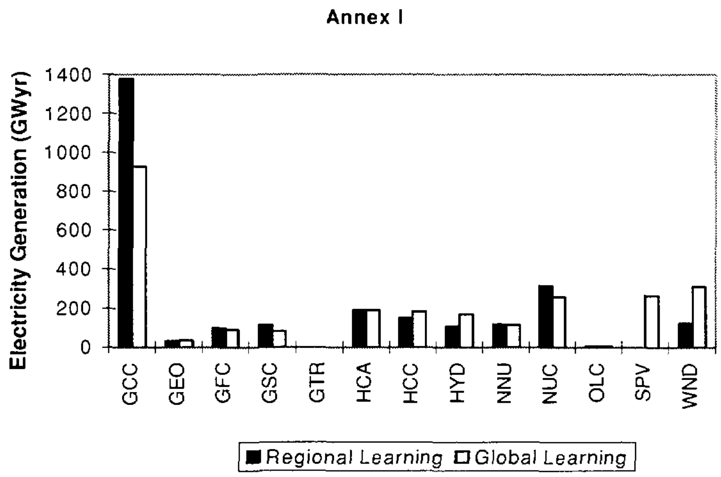

Figure 51. *Electricity generation mix in 2050. Annex I group. Global Vs Regional learning*

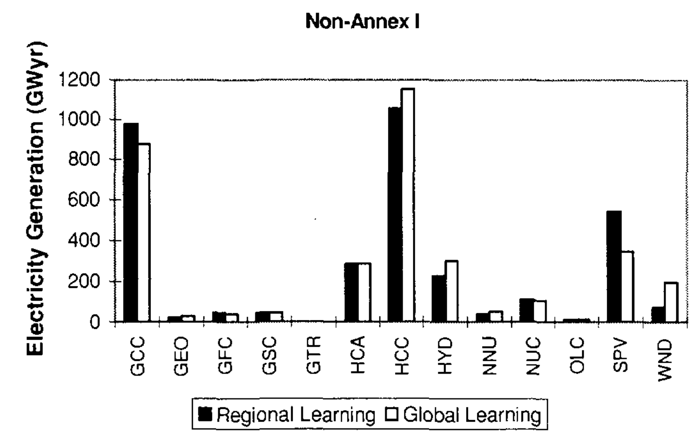

Figure 52. *Electricity generation mix in 2050. Annex I group. Global Vs Regional learning*

As expected, restricting the size of the learning regions, affects the cost competitiveness of the technologies and, consequently, their ranking and generation output. In this particular case, the wind turbine experiences a much lower global growth. In the case of the solar PV, the aggregated output is also reduced but to a lesser extent. However, investments in this technology are carried out almost exclusively in the non Annex I regions while in the global learning situation they were present in both groups of countries. On the other hand, gas combined cycle turbines, already very competitive, are able to increment their electricity production in the regional learning case. This model result could be interpreted as an illustration of the fact that, if not enough opportunities exist for a given technology to accumulate the experience necessary to go down its learning curve and become competitive, it may be "locked out" from the system.

6. Conclusions

The assessment of opportunities for emerging technologies in shaping future energy systems is a complex task involving the examination of interactions between a number of technical, economic, environmental and social driving forces. The understanding of the dynamics of technology is a central issue in policy decisions concerning the definition of future sustainable trajectories for the energy systems (Kemp, 1997). There is a necessity for better treatment of technological dynamics in the energy decision frameworks.

A series of driving factors, concerning the cost and efficiency evolution, the market penetration, the influence of R&D expenditures, the inertia and capacity of change of the system, among others, have been traditionally handled in an exogenous manner or not considered at all in the traditional analytical approaches. Technological development, however, is not an autonomous but an endogenous process, where both R&D and the market intervene and influence each other (Grübler, 1998, Grubb, 1997).

The endogenous technological learning concept constitutes an advance towards a more comprehensive framework for the treatment of technological change in energy models. The concept helps to determine possibilities and requirements for new energy technologies, assess the maturation costs of a given technology and define policy measures that contribute to environmentally compatible technological change.

This experience also showed the difficulties of an endogenous representation of such factors, revealing both computational challenges for incorporating them into large scale energy optimisation models and the necessity of a profound understanding of technology evolution and interactions in order to support the model analyses.

As stressed by Messner and Schrattenholzer (1998), there is an important point regarding the application of the technological learning concept. The sole awareness of the existence of learning effects, drives the analyst to conceive the structure of the model in a different way, avoiding, for instance, "learning for free" situations if a standard non-learning model is being used.

6.1 Methodological aspects

Experience curves have been endogenised in the ERIS and MARKAL models. For ERIS, non-linear and Mixed Integer Programming formulations are used. The MIP approach is being incorporated also into the RMARKAL version of the MARKAL model.

The ERIS prototype has been beneficial as a tool to test and compare alternative approaches. Along the project, ERIS has evolved into a more elaborated model which allows to carry out some policy analyses, but it is still flexible enough to allow the incorporation of new features before translating them to more complex energy optimisation models.

The experience at PSI with the two formulations may be summarised as follows:

- Non-linear Program

The NLP formulation of the model enabled the identification of local optimal solutions to the problem. The model introduced new technologies due to cumulative learning effects, producing different system structures than those obtained with the static LP model. The tests of the NLP version already revealed the high sensitivity of the model to the inputs on learning (e.g. the progress ratio). The application of global optimization algorithms to the non-convex non-linear problem should be investigated.

- Mixed Integer Program

The MIP approach, also implemented in the MARKAL model, provides a linearisation of the problem, ensuring a global optimum solution for the otherwise non-linear, non-convex mathematical program. The cumulative cost curve is approximated by linear segments and binary variables are used for the logical conditions that enforce the segments sequence. The approach is, however, considerably more computational intensive and a number of parameters affect the accuracy of the piece-wise linear representation. Of particular importance are the maximum cumulative capacity for the learning technologies, the number of segments and the segmentation procedure, which have to be defined carefully for an adequate approximation of the original non-linear learning curve.

The progress ratio, determining the speed at which the learning process takes place, proves to be one of the most important and sensitive assumptions. A careful technology characterisation and studies of the main driving factors of change and opportunities for new technologies in specific sectors must support the learning rate assumptions. Besides the progress ratio, other influential parameters are the discount rate and the maximum growth rate of the technologies. A high inter-temporal discounting may delay or prevent the introduction of new technologies, currently with high investment costs, even if they have a high learning potential. The maximum growth rate of the technologies determines to a given extent the possibilities of learning along the time horizon. The typical "lock-in" behaviour of the model calls for a careful examination of the assumptions regarding progress ratio, maximum cumulative capacity and maximum penetration rates of a technology.

- Stochastic formulation

The inherent uncertainty of progress ratios as well as other key factors such as demands, emission targets, resource prices etc., requires sensitivity and/or stochastic analysis. In the case of the learning rates, for instance, sensitivity analyses in a deterministic framework are useful to establish a "break-even" value for the progress ratio. That is, the progress ratio at which a given technology may become competitive.

The application of a stochastic programming approach allows to handle uncertainty in these key parameters. When the stochastic approach is combined with endogenous learning, two basic driving factors of technological change can be examined in a common framework: uncertainty and increasing returns. Here, a traditional two-stage stochastic programming approach, with uncertainty resolution at a fixed point in time, was applied in the ERIS model prototype to account for uncertainties in CO_2 constraints, demand and learning rates. The results demonstrate the importance of interactions between learning effects and uncertainty in other technical or economical variables and the effects of representing uncertainty in the learning itself. However, when combined with the MIP approach, the computational burden for solving the stochastic model increased considerably. Other stochastic optimisation approaches should be examined and further work is required regarding more efficient solution procedures.

6.2 Post-Kyoto analysis with ERIS

Using the multi-regional version of ERIS, some indicative analyses concerning the future structure of the global electricity generation system under a fast growth demand scenario are carried out. Possible consequences of the Kyoto protocol on the structure of the generation mix and the effects of international emission trading for its fulfilment have been outlined, considering the effect of endogenous technological learning.

The results of these analyses show that fossil fuels, mainly coal and natural gas, will continue to hold a significant share of the global electricity supply in the next fifty years. Natural gas Combined Cycle turbines will experience a very dynamic growth rivalling coal plants as the prevalent generation technology. Nuclear power plants remain a robust option for electricity generation if the path to de-carbonisation is to be followed. However, there are also opportunities for new, emerging technologies. Advanced, more efficient, coal power plants are likely to gain share. Wind turbines constitute a readily cost-competitive alternative in several markets. Solar photovoltaics may be brought about in a massive way in a CO_2 constrained world. Gas fuel cells could also play an important role.

The analysis of Kyoto-for-ever scenarios indicates that a significant departure from carbon intensive generation options is required to fulfil the CO_2 emission targets. However, global emissions from electricity systems will continue to grow substantially. With an endogenous representation of technology dynamics, early up-front investments are made to stimulate the necessary technological progress of emerging low -or free- carbon generation options, which are then able to play an active role in the mitigation strategy. This early action stimulates technological learning that proves beneficial in terms of both lower costs and emissions in the long run.

The possibility of trading emission permits, either between Annex I regions or extending the trade to non Annex I regions, will allow some regions to undertake less radical changes in their electricity sectors than what would be required otherwise. Nonetheless, trade does not rule out action in the regions with commitments. However, trade may provide incentives for the penetration of emerging learning technologies in different regions, stimulating accumulation of experience with them, and thus contributing to the progress along their learning curves towards long run cost competitiveness. In particular, international co-operation for emissions abatement between Annex I and Non-Annex I countries may drive to significant deployment of new technologies in developing countries, multiplying the opportunities for technological learning as penetration occurs in markets with significant potential and attractive niche markets.

In a multi-regional framework, the representation of endogenous technological learning leads to interesting patterns of response of the model. Due to the underlying increasing returns mechanism, and the allowance of full spill-over of learning, installations of a given technology in a certain region will contribute to make it competitive in another region(s) and thus stimulate its deployment there and a further increase in cost competitiveness. The scale at which learning is allowed (global, regional) will certainly affect the possible development. The spatial dimension of technological learning and the possibilities of learning "spill-over" are aspects that deserve further investigation.

The results also show the importance of taking into account the uncertainty of the technological learning process and other technical and economical driving factors. The consideration of uncertain learning rates may drive the model to follow a more prudent and gradual path of investments in learning technologies. Uncertainties in other factors, such as emission targets or demands have also an impact, stimulating or delaying technological learning. When uncertainty in emission reduction commitments is considered, the results point also in the direction of undertaking early action as a preparation for future contingencies. If demand is uncertain, the possibility of a higher demand may also stimulate earlier technological learning. Following the statement of Grübler (1998), who stresses that uncertainty is, together with learning, at the core of the endogenous mechanisms of technological change, future work should also be devoted to a more thorough exploration of the effects of uncertainty both in learning rates and other driving forces such as demands and environmental constraints and to the application of more sophisticated stochastic approaches for the learning patterns.

Competition against well established electricity generation technologies will not be easy for emerging, less carbon intensive but more expensive alternatives. If they are to play a significant role in future energy markets, emerging technologies will require investments, both in R&D and niche markets, to foster their development. Technology policy instruments may also be required to provide specific incentives to the production of electricity from new technologies (Loiter and Norberg-Bohm, 1999). Therefore, their successful introduction requires a strategy that promotes innovation and learning at multiple technological, social and institutional levels.

6.3 Policy insights

The experiences with both models proved the significant influence of endogenous technological learning in the evolution of the energy systems. New, initially expensive, technologies, hardly considered by the linear programming model may be introduced as a consequence of the endogenous cost evolution in the model. Early up-front investments are made, which allow those technologies to accumulate the experience they require to become competitive in the long run. On the other hand, if learning conditions are not attractive enough, a technology can be "locked-out" from the system.

Endogenous learning may drive to lower estimates of CO_2 abatement costs. Also, even in the absence of an emissions constraint, lower long term emission profiles may appear when, as a result of the endogenous technology dynamics, low-carbon or carbon-free technologies are extensively introduced.

The results thus, illustrate the influence of the treatment given to the technology dynamics in the policy recommendations that can be derived from the models. When examining strategies to mitigate environmental impacts from the energy systems, an endogenous dynamics of technology, which recognises the gradual and cumulative nature of technological change, favours early actions to stimulate the technological learning necessary to improve cost and performance of new, more environmentally compatible and more efficient technologies. Hence, as new technologies will become competitive only if experience with them is possible, the results reveal the need for early investments on emerging environmentally compatible technologies, both in R&D and niche markets, in order to ensure that they move along their learning curves and reach long term competitiveness with well established technologies.

6.4 Further work

The ERIS prototype could be extended to include other features. For instance, more detailed demand and supply technologies and relationships may be represented. For such purpose, elements from the demand side and market equilibrium mechanisms of the PRIMES model[24] and from the supply-side of MARKAL could be incorporated.

In addition, procedures to hard or soft-link the learning approach with traditional energy or energy-economy modelling approaches have to be examined further. One possibility of further development could be to link ERIS to the MERGE3 model. In such case, one possibility could be to specify a modified macro-economic function including knowledge as one of the basic components of economic activity.

As the computational complexity of the MIP approach may increase substantially for a large scale model, the solution of reduced scale models such as ERIS could be used to define the time dependence of investment cost for technologies in a dynamic large scale detailed models. This approach was already followed by IIASA with the MESSAGE model (Schrattenholzer, 1998). The possibilities and level of error of such an approximation method should be assessed.

Further work with the MARKAL model could be directed to the introduction of a stochastic treatment for the progress ratio and the incorporation of learning into the multi-regional framework, both features already tested in ERIS. Developments in MARKAL are

[24] PRIMES is a large scale model of the energy systems of the EU states linked together through energy markets. It was developed by several partners for the European Commission (1995).

important because, being this a widely extended tool, used by several countries to support decision making concerning greenhouse gases mitigation options in the energy systems, the analytical techniques employed to handle the technological variable are critical for devising sound policy recommendations.

Another aspect is related to the possibility of linking the learning of several related technologies. Technological clusters may be shaped where a number of technologies interact and cross-enhance each other, contributing to their mutual development (Nakicenovic, 1997, Grübler, 1998). It becomes very important to study how these interrelated clusters evolve, in order to gain insights how to promote the introduction of clusters of new environmentally sound energy technologies.

Seebregts at al. (1999b) have applied the concept of key technologies to the European MARKAL database. They are defined as those technologies that are a component in many other technologies. In their analysis, a learning curve is specified for each key technology. The technologies specified in the Reference Energy System with a common key technology are grouped in a cluster and the sum of capacities across the cluster used to update the costs of the key technology.

This procedure seems to be a good way of linking the learning of groups of technologies, taking into account one important aspect of technology interdependence, namely the presence of a key common component, whose learning spills over the technologies using it. However, other mechanisms acting on the conformation of technological clusters could be incorporated in the models. Further attention should be given to the complex interrelations that drive to co-evolution of technologies.

The learning curve for one technology may be modified along its life cycle (Ayres and Martinàs, 1992, Nakicenovic, 1997). Some technologies may experience a slowdown or acceleration of the cost reduction process. This could be considered by specifying different learning rates for different stages of the technology development. A threshold value of cumulative capacity must be defined. Below this threshold an initial learning rate will be specified and above the threshold, a second one (higher/lower) can be used. However, the question remains how to choose the capacity threshold values where a technology modifies its learning speed. A more profound assessment of the possible changes in the learning process along the life cycle of a given technology should be carried out.

The definition (or not) of lower limits to the specific cost must be analysed further. Here, in some cases, an arbitrary "floor" cost was introduced for some technologies with high learning potential, whose costs would otherwise reach fairly low values. However, the imposition of limits to the learning of the technologies should be linked either to a study of their cost structure, in order to establish the cost components more likely to be reduced and the corresponding magnitude of the reduction or subjected to expert judgement regarding the expected future costs.

Other aspects of technological change, related to intervening factors such as R&D expenditures, or the spatial and temporal patterns of technological diffusion (Grübler, 1991, 1998), have to be incorporated in order to develop a more comprehensive analysis framework. It would be interesting, for instance, to correlate the different levels of learning with the R&D spending on different technologies and study the options to reduce the climate change risk as function of R&D spending. It is also important to examine the interaction between technological learning and uncertainties in greenhouse gases reduction targets, demands and other economic variables, in order to assess the impacts of such mutual influences both on the technological evolution and the costs of abatement strategies.

For that purpose, the modified learning curve used by Grübler and Gritsevskii (1997), could be applied. Such curve considers cumulative expenditures instead of cumulative capacity as the proxy for accumulation of knowledge, allowing to take into account the effects of R&D expenditures in addition to those of investments in commercial capacity deployment.

For the analyses to be meaningful, support has to be given to the assumptions about the behaviour of the technologies. This support requires a careful assessment of possibilities for emerging technological systems, documenting expected cost reductions and/or improvements of performance as well as possible interactions with other technologies. Analyses should rely upon a detailed description of technological options and assessment of the public and private support mechanisms required to materialise them. The analysis should try to identify the candidate technologies, to elaborate plans for R&D support under risk aversion and hedging, and to define approaches that allow maximum flexibility in reshaping decisions with a minimum regret.

Finally, although challenging, it is very important to continue advancing in the endogenisation of technological change in energy models. The treatment given to technology dynamics affects our understanding of a number of issues concerning the evolution of energy systems and their long term impacts. Understanding is required of the continuos technological substitution processes where some energy technologies may develop and reach a dominant position being "locked-in", while other technologies are "locked-out" and the effects of the emergence and decay of technological regimes on the costs and timing of strategies to mitigate the environmental impacts of the energy systems. An adequate framework is necessary to gain insights about the underlying forces that drive this evolution.

7. References

1. Argotte L., Epple D. (1990). "Learning Curves in Manufacturing". *Science*. Vol. 247, pp 920-924.
2. Arthur W.B. (1988). "Self-Reinforcing Mechanisms in Economics". In *The Economy as an Evolving Complex System*. Addison-Wesley.
3. Ayres R., Martinàs K. (1992). "Experience and the Life Cycle: Some Analytical Implications".*Technovation*. Vol. 12 No 7. pp 465-486.
4. Barreto L., Kypreos S. (1999). *"A Post-Kyoto Analysis with the ERIS Model Prototype"*. TEEM Project of EC-JOULE-III. The ERIS Model Prototype. Paul Scherrer Institute. Paper submitted to the *Int. J. of Global Energy Issues*.
5. Cameron G. (1996). *"Innovation and Economic Growth"*. Discussion Paper No 277. Centre for Economic Performance. London School of Economics and Political Science. London.
6. Capros P., Filippopoulitis A., Georgakopoulos T. (1998a).*"Specification of the IIASA Model Prototype in GAMS"*. Version II. National Technical University of Athens. TEEM Project of EC-JOULE III. The ERIS Prototype Model. Athens, May, 1998.
7. Capros P., Filippopoulitis A., Georgakopoulos T. (1998b). *"Mixed Complementarity Formulation with Stochastic Learning and Risk Aversion"*. National Technical University of Athens. TEEM Project of EC-JOULE III. The ERIS Prototype Model. Athens, July,1998.
8. Christiansson L. (1995*). "Diffusion and Learning Curves of Renewable Energy Technologies"*. Working Paper WP-95-126. International Institute for Applied Systems Analysis. Laxemburg, Austria.
9. Cody G., Tiedje T. (1997). "A Learning Curve Approach to projecting Cost and Performance for Photovoltaic Technologies". *Future Generation Photovoltaic Technology: First NREL Conference*. The American Institute of Physics.
10. Conley P. (1970). "Experience Curves as a Planning Tool". *IEEE Spectrum*. June, 1970.
11. Criqui P. (1999). "*POLES Results of the REFXII Scenario*", working notes, (spreadsheet files)
12. Cunningham J. (1980). "Using the Learning Curve as a Management Tool". *IEEE Spectrum*. June, 1980
13. DOE (1996). "*Fuel Cell Systems Program for Stationary Power*". DOE-FE-0350. Deputy Assistant Secretary for advanced research and special technologies. Assistant Secretary for Fossil Energy U.S Department of Energy. Washington D.C. U.S
14. EIA (1998). "*Impacts of the Kyoto Protocol on U.S. Energy Markets and Economic Activity*". SR/OIAF/98-03. Office of Integrated Analysis and Forecasting. Energy Information Administration. U.S. Department of Energy.
15. Ellis J., Tréanton K. (1998). "Recent Trends in Energy-Related CO_2 Emissions". *Energy Policy*, Vol. 26, No 3, pp 159-166.
16. European Commission (1995). *'The PRIMES project'*. EUR 16713 EN. Joule II Programme. August,1995. Brussels, Belgium.

17. Fishbone, L.G., Abilock, H. (1981). "MARKAL, a Linear-Programming Model for Energy Systems Analysis: Technical Description of the BNL Version", *International Journal of Energy Research*, Vol. 5, pp. 353-375.
18. Grubb M. (1997). "Technologies, Energy Systems and the Timing of CO_2 Emissions Abatement. An Overview of Economic Issues". *Energy Policy*. Vol. 25, No 2, pp 159-172.
19. Grübler A. (1991). "Diffusion. Long-Term Patterns and Discontinuities". *Technological Forecasting and Social Change*. Vol. 39, pp 159-180.
20. Grübler A. (1998). "*Technology and Global Change*". International Institute of Applied Systems Analysis. Cambridge University Press.
21. Grübler A., Gritsevskii A. (1997). "*A Model of Endogenous Technological Change Through Uncertain Returns on Learning (R&D and Investments)*". Paper presented at the International Workshop on induced Technical Change and the Environment. 26-27, June. International Institute for Applied Systems Analysis. Laxemburg, Austria.
22. Grübler A., Messner S. (1998). "Technological Change and the Timing of Mitigation Measures". *Energy Economics*. Vol. 20. Nos. 5,6. pp 495-512.
23. Grübler A., Nakicenovic N.,Victor D. (1999). "Dynamics of Energy Technologies and Global Change".*Energy Policy*. Vol. 27, pp 247-280
24. IIASA-WEC International Institute for Applied Systems Analysis and World Energy Council (1998). "*Global Energy Perspectives*". Nakicenovic N., Grübler A. and McDonald A., eds. Cambridge UniversityPress.
25. ILOG (1997). "*Using the CPLEX Callable Library*". Version 5.0. CPLEX Division. ILOG Inc. USA.
26. Islas J. (1999). "The Gas Turbine: A New Technological Paradigm in Electricity Generation". *Technological Forecasting and Social Change*. Vol. 60, pp 129-148.
27. Isoard S. (1996). "Diffusion of Energy Technologies: The Influence of Increasing Returns". *IPTS Report*. Vol. 10. December, 1996. Institute for Prospective Technological Studies. Joint Research Center. European Union. http://www.jrc.es/pages/f-report.en.html
28. Kemp R. (1997a). "The Transition from Hydrocarbons: The Issues for Policy". In *Models of Sustainable Development*. Faucheux S., Pearce D., Proops J. (Eds). Edward Elgar. Cheltenham, United Kingdom
29. Kemp R. (1997b). "*Environmental Policy and Technical Change. A Comparison of the Technological Impact of Policy Instruments*". pp 263-278. Edward Elgar. Cheltenham, UK.
30. Kypreos S. (1998). "*Specification of the Model Prototype with Stochastic Learning and Risk Aversion*". PSI Version. TEEM Project of Joule-III. The ERIS Prototype Model. Paul Scherrer Institute. Villigen, Switzerland. June, 1998
31. Kypreos S., Barreto L. (1998a). "*Mixed Integer Programming for Experience Curves in the ERIS Model Prototype*". TEEM Project of Joule-III. The ERIS Prototype Model. Paul Scherrer Institute. Villigen, Switzerland. August, 1998
32. Kypreos S., Barreto L. (1998b). "*Mixed Integer Programming for Learning Curves in MARKAL-Documentation*". TEEM Project of Joule-III. Paul Scherrer Institute. Villigen, Switzerland.

33. Kypreos S., Barreto L. (1998c). "*A Simple Global Electricity MARKAL Model with Learning*". Paper presented to the Joint IEA-ALEP/ETSAP Workshop. Antalya, Turkey. October, 1998
34. Kypreos S., Barreto L. (1998d). "*Experience Curves in MARKAL and Links to Macro-Economic Models*". Workshop on Modelling Technological Learning. International Institute for Applied Systems Analysis. Laxemburg, Austria. March 19-21, 1998.
35. Kypreos S., Barreto L., Capros P., Filipopoulitis A., Georgakopoulos T. , Messner S. (1999). " *ERIS: A Model Prototype with Endogenous Technological Change*". Paul Scherrer Institute. TEEM Project of JOULE-III. Villigen, Switzerland. Paper submitted to the *Int. J. of Global Energy Issues*.
36. Lloyd A. (1999). "The Power Plant in your Basement". *Scientific American*. July, 1999. pp 64-69.
37. Loiter J., Norberg-Bohm V. (1999). "Technology Policy and Renewable Energy: Public Roles in the Development of New Energy Technologies". *Energy Policy*. Vol. 27. pp 85-97.
38. Manne A., Richels R. (1997). "On Stabilizing CO_2 Concentrations.-Cost-Effective Emission Reduction Strategies" *Environmental Modelling and Assessment*. Vol. 2 .pp 251-265
39. Marchetti C. (1980). " Society as a Learning System: Discovery, Invention, and Innovation Cycles Revisited". *Technological Forecasting and Social Change*. Vol. 18, pp 267-282.
40. Mattsson N. (1997). "*Internalising Technological Development in Energy Systems Models*". Thesis for the degree of Licentiate of engineering. Chalmers University of Technology. Göteborg, Sweden.
41. Mattsson N. (1998). "*GENIE: an Energy System Model with Uncertain Learning*". Proceedings of the IEA/ETSAP 5th Workshop. Berlin, Germany. 6-7 May, 1998.
42. Mattsson N., Wene C.-O. (1997). "Assessing New Energy Technologies using an Energy System Model with Endogenized Experience Curves". *International Journal of Energy Research*. Vol. 21, pp 385-393.
43. Messner S. (1997). "Endogenised Technological Learning in an Energy Systems Model". *Journal of Evolutionary Economics* Vol. 7, pp 291-313.
44. Messner S., (1998). "*IIASA Maquette Model Prototype on Endogenized Technological Learning*". TEEM Project of Joule-III. The ERIS Prototype Model. International Institute for Applied Systems Analysis. Laxemburg, Austria.
45. Messner S., Schrattenholzer L. (1998). "*Experiences from including Technology Progress Dynamics into the Global Optimisation Model MESSAGE*". ECS Contribution to the Mid-Term Assessment Report of the TEEM Project. IIASA. Laxemburg, Austria. Draft. October, 1998.
46. Messner S., Strubegger M. (1995). "*User's Manual of MESSAGE III*". WP-95-69. International Institute for Applied Systems Analysis (IIASA). Laxemburg, Austria.
47. Nakicenovic M. (1997). "*Technological Change as a Learning Process*". Paper presented at the International Workshop on Induced Technical Change and the Environment. 26-27 June. International Institute for Applied Systems Analysis. Laxenburg, Austria.

48. Neij L. (1997). "Use of Experience Curves to Analyse the Prospects for Diffusion and Adoption of Renewable Energy Technology". *Energy Policy*. Vol. 23, No 13. pp 1099-1107.
49. Neij L. (1999). "Cost Dynamics of Wind Power".*Energy*. Vol. 24 pp 375-389.
50. Petersik T. (1997). *"The Impact of International Learning on Technology Cost"*. Energy Information Administration. U.S Department of Energy. http://www.eia.doe.gov/oiaf/issues97/learning.html
51. Piater, A. (1991) "The Innovation Process: Analysis, Driving Forces, Obstacles, Assessment". In Henry B. (Editor). *Forecasting Technological Innovation*. Kluwer Academic Publishers. The Netherlands.
52. Robinson J. (1980). "Technological Learning, Technological Substitution, and Technological Change". *Technological Forecasting and Social Change*. Vol. 18, pp 39-49.
53. Rogner H.H. (1996b). "Hydrogen Technologies and the Technology Learning Curve". In *Hydrogen Energy Progress XI. Proceedings of the 11th World Hydrogen Energy Conference*. Stuttgart, Germany.
54. Rogner H-H. (1996a) "*Stabilisation of Atmospheric CO_2 Concentrations: The Role of Technology Change*". Paper presented at CoP 2, Special Session on Quantified Emission Limitation and Reduction Objectives (QELROS), July 9-16, 1996. Geneva, Switzerland
55. Schrattenholzer L. (1998). *"Analysis of Past Learning Rates"*. ECS Contribution to the progress report TEEM. Draft. Proceeding of the Workshop on Technology Improvement Dynamics. IPTA, Seville. December 14-15, 1998.
56. Schrattenholzer L. (1998). "Checking the Consistency of MESSAGE Results with Assumed Learning Rates". *Proceedings of the IIASA Workshop on Modeling Technological Learning*. TEEM Project of EC-JOULE III. Laxenburg, Austria.
57. Seebregts A. (1998). *Implementation of an NLP formulation of Technological Experience Curves in MMARKAL 2.2.* Working paper for ECN and PSI use. Netherlands Energy Research Foundation. June 1998.
58. Seebregts A., Stoffer A., Schaeffer G., Kram T. (1998) "*Endogenous Technological Learning: Experiments with MARKAL*". Contribution to task 2.3 of the Project TEEM of EC-JOULE-III. ECN-C-98-064. ECN Policy Studies, Petten, The Netherlands.
59. Seebregts A.J., Kram T.,Schaeffer G.J., Stoffer A., Kypreos S., Barreto L., Messner S., Schrattenholzer L.(1999a) *"Endogenous Technological Change in Energy System Models. Synthesis of Experience with ERIS, MARKAL, and MESSAGE"*. Contribution to the TEEM Project of Joule III. ECN-C-99-025. ECN. Petten, The Netherlands.
60. Seebregts A., Bos S., Kram T., Schaeffer G. (1999b). *"Results for the Large Scale MARKAL Model for Western Europe"*. Section 10.2. Chapter 10 (The Post-Kyoto Scenarios: Endogenous learning with Perfect Foresight). TEEM final Report. Draft. ECN. Petten, The Netherlands.
61. Sierksma G. (1996) "*Linear and Integer Programming: Theory and Practice*". Editorial Dekker. New York.
62. Sweet W. (1999). "Technology 1999. Analysis & Forecast: Power&Energy". *IEEE Spectrum*. Institute of Electrical and Electronic Engineers Inc. January, 1999.

63. TEEM (1997). "*Energy Technology Dynamics and Advanced Energy System Modelling - Technical Annex*". JOULE III Project. September, 1997.
64. Thomas M., Post H., DeBlasio R. (1999). "Photovoltaic Systems: An End-of-Millennium Review". *Progress in Photovoltaics: Research and Applications*. Vol. 7, pp 1-19.
65. Van Geffen J.W.A. (1995). "*A Stochastic Programming Analysis of Hedging for Climate Change*". Netherlands Energy Research Foundation ECN. The Netherlands.
66. Victor D., Nakicenovic N., Victor N. (1998). "*The Kyoto Protocol Carbon Bubble: Implications for Russia, Ukraine and Emission Trading*". Interim Report. IR-98-094. International Institute for Applied Systems Analysis. Laxemburg, Austria.
67. Williams H.P. (1985). "*Model Building in Mathematical Programming*". John Wiley&Sons.
68. Wright T.P. (1936). "Factors affecting the Cost of Airplanes". *Journal of the Aeronautical Sciences*. Vol. 3, February, pp 122-128

List of Abbreviations

CPLEX	Solver for LP and MIP problems. CPLEX is a trademark of ILOG
DOE	U.S. Department of Energy
ECN	The Netherlands Energy Research Foundation
ERIS	Energy Research and Investment Strategy. TEEM model prototype
ESD	Energy for Sustainable Development
ETSAP	Energy Technology Systems Analysis Programme (ETSAP) of the IEA
GENIE	Global Energy System with Internalized Experience Curves Model
IEA	International Energy Agency of the OECD
IEPE/CNRS	Institut d'Économie et de Politique de l'Énergie
IER	Institut für Energiewirtschaft und Rationelle Energieanwendung
IIASA	International Institute for Applied Systems Analysis
IPTS	Institute for Prospective Technology Studies
KUL	Catholic University of Leuven
LP	Linear Programming
MARKAL	MARKet ALlocation model
MCP	Mixed Complementarity Problem
MERGE3	Model for Evaluating Regional and Global Effects of GHG Policies
MESSAGE	Energy optimisation model developed at IIASA
MINOS5	Solver for LP and NLP problems
MIP	Mixed Integer Programming
NEMS	National Energy Modelling System of the DOE
NLP	Non Linear Programming
NTUA	National Technical University of Athens
POLES	Prospective Outlook on Long-term Energy Systems Model
PRIMES	Energy Model of the European Union covering all member-states
PSI	Paul Scherrer Institute
TEEM	Energy Technology Dynamics and Advanced Energy System Modelling
WEC	World Energy Council

Appendix 1. The RMARKAL code

This section presents the implementation of the MIP approach in the RMARKAL model carried out at PSI. This implementation corresponds to the formulation described in numeral 3.7. The SETS, PARAMETERS, VARIABLES, and EQUATIONS that must be added to the normal RMARKAL code are described.

A1.1 Model SETS

TEG	Endogenous learning technologies
KP	Index of segments
RP	Index of segments - alias

TEG and RP are declared in MMSETS1.INC. KP has to be declared in the *.gen file before calling MMINIT1.INC.

The elements of KP are dictated by the maximum number of segments given for one technology. That is, if there are two technologies with experience curves, one of them with 4 segments and the other with 6 segments, then the set KP will be /0*6/.

A1.2 Model PARAMETERS

Declared and defined in MMCOEF1.INC

SC0(TEG)	Initial specific cost
PRAT(TEG)	Progress ratio
PBT(TEG)	Learning curve parameter b (computed from PRAT(TEG))
PAT(TEG)	Learning curve parameter a (computed from SC0 and PBT)
CCAP0(TEG)	Initial cumulative capacity
CCOST0(TEG)	Initial cumulative cost
CCAPM(TEG)	Maximum cumulative capacity
CCOSTM(TEG)	Maximum cumulative cost
CCAPK(KP, TEG)	Kink points for cumulative capacity
CCOSTK (KP, TEG)	Kink points for cumulative cost
BETA(KP, TEG)	Beta parameter for cumulative cost interpolation
ALPH(KP, TEG)	Alpha parameter for cumulative cost interpolation
SEG(TEG)	Number of segments per technology
WEIG(KP, TEG)	Weighting factors for the segmentation

A1.3 Model VARIABLES

Declared in MMVARS1.INC

CCAP(TP, TEG)	Cumulative capacity
LAMBD(TP, TEG, KP)	Lambda variables for capacity interpolation
DELTA (TP, TEG, KP)	Delta binary variables
CCOST(TP, TEG)	Cumulative cost
IC(TC, TEG)	Undiscounted investments
SV_INV(TP, TEG)	Salvage on learning investments

A1.4 Model EQUATIONS

Defined in MMEQTEG1.INC, listed in MMEQUA1.INC and MODEL1.MRK

EQ_CUINV(TP, TEG)	Definition of cumulative capacity
EQ_CC(TP, TEG)	Interpolation of cumulative capacity
EQ_DEL(TP, TEG)	Sum of delta variables to 1
EQ_COS(TP, TEG)	Cumulative cost interpolation
EQ_LA1(TP, TEG, KP)	Logical conditions using delta variables 1
EQ_LA2(TP, TEG, KP)	Logical conditions using delta variables 2
EQ_EXPE1(TP, TEG, KP)	Experience grows-Additional constraint 1
EQ_EXPE2(TP, TEG, KP)	Experience grows-Additional constraint 2
EQ_IC1(TB, TEG)	Undiscounted investments for the first period
EQ_IC2(TP, TEG)	Undiscounted investments for other periods
EQ_SV(TP, TEG)	Salvage on learning investments
EQ_SV2(TP, TEG)	Additional condition for salvage

A new additional file is used for the main formulation of the MIP approach. The other changes are done on existing (renamed) files.

1. File MMEQTEG1.INC

```
*====================================================================*
*LB* MMEQTEG1.INC technological change equations - Formulation 1 (N. Mattsson)
*   %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 ''
*   %5 - REGional indicator => '' or '' or 'REG,'
*   %6 - regional scaling => '' or '' or '(REG)'
* %7 - loop control set => 'TPCON(TP,CON)' or 'TPNCON(TP,SOW,CON)' or        *
'TPCON_R(REG,TP,CON)'
*GG* V3.0 modularise calls to equations
*====================================================================*
*$ONLISTING
* Cumulative capacity definition

%1_CUINV(%5TP, %5TEG)$(ORD(TP) GE TCH_STRT%3(%5TEG))..CCAP(%5TP, %5TEG) =E=
SUM(TC$((ORD(TC) LE ORD(TP))$ (ORD(TC) GE TCH_STRT%3(%5TEG))), INV(TC,
%5TEG))+CCAP0(TEG);
```

```
* Cumulative Capacity Interpolation

%1_CC(%5TP, %5TEG)$(ORD(TP) GE TCH_STRT%3(%5TEG))..CCAP(%5TP, %5TEG) =E= SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(TEG)+1)), LAMBD(%5TP, %5TEG, KP));

* Force sum of binary variables delta to 1

%1_DEL(%5TP, %5TEG)$(ORD(TP) GE TCH_STRT%3(%5TEG))..SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(TEG)+1)), DELTA(%5TP, %5TEG, KP)) =E= 1;

* Cumulative Cost Interpolation

%1_COS(%5TP, %5TEG)$(ORD(TP) GE TCH_STRT%3(%5TEG))..CCOST(%5TP, %5TEG)=E=SUM(KP$((ORD(KP) GE 2)$(ORD(KP) LE SEG(TEG)+1)), LAMBD(%5TP, %5TEG, KP)*BETA(KP, %5TEG)+DELTA(%5TP, %5TEG, KP)*ALPH(KP, %5TEG));

* Constraints on lambda

%1_LA1(%5TP, %5TEG, KP)$((((ORD(KP) GE 2))$(ORD(KP) LE SEG(TEG)+1))$(ORD(TP) GE TCH_STRT%3(%5TEG)))..LAMBD(%5TP, %5TEG, KP)=G=CCAPK(KP-1, TEG)*DELTA(%5TP, %5TEG, KP);

%1_LA2(%5TP, %5TEG, KP)$((((ORD(KP) GE 2))$(ORD(KP) LE SEG(TEG)+1))$(ORD(TP) GE TCH_STRT%3(%5TEG)))..LAMBD(%5TP, %5TEG, KP)=L=CCAPK(KP, TEG)*DELTA(%5TP, %5TEG, KP);

* Additional constraints to improve solution time

 %1_EXPE1(%5TP, %5TEG, KP)$((((ORD(KP) GE 2))$(ORD(KP) LE SEG(TEG)+1))$(ORD(TP) GE TCH_STRT%3(%5TEG)))..SUM(RP$(ORD(RP) LE ORD(KP)$(ORD(RP) GE 2)), DELTA(%5TP, %5TEG, RP)) =G= SUM(RP$(ORD(RP) LE ORD(KP)$(ORD(RP) GE 2)), DELTA(%5TP+1, %5TEG, RP));

 %1_EXPE2(%5TP, %5TEG, KP)$((((ORD(KP) GE 2) AND (NOT TLAST(TP)))$(ORD(KP) LE SEG(TEG)+1))$(ORD(TP) GE TCH_STRT%3(%5TEG)))..SUM(RP$(ORD(RP) GE ORD(KP)), DELTA(%5TP, %5TEG, RP)) =L= SUM(RP$(ORD(RP) GE ORD(KP)), DELTA(%5TP+1, %5TEG, RP));

* Investments to be discounted 1st period the technology is available

 %1_IC1(%5TP, %5TEG)$ (ORD(TP) EQ TCH_STRT%3(%5TEG))..IC(TP, TEG) =E= CCOST(TP, TEG) - CCOST0(TEG);

* Investments to be discounted , other periods

%1_IC2(%5TP, %5TEG)$ (ORD(TP) GT TCH_STRT%3(%5TEG))..IC(TP, TEG) =E= CCOST(TP, TEG)- CCOST(TP-1, TEG);

* Salvage of learning investments

%1_SV(%5TP, %5TEG)$(((ORD(TP) + TCH_LIFE(TEG) - CARD(TP)-1) GT 0))..SV_INV(TP, TEG)
 =E= ( (IC(TP, TEG)
*GG* V1.5m handle sunk/released material
    +
```

```
    SUM(ENC $ SNK_ENC(ENC,TEG),
      SAL_SNK(ENC,TP)
      * (PRC_INP1(TEG,ENC) + CON_INP1(TEG,ENC) + DMD_MATID(TEG,ENC))
      * (1$(NOT ENU(ENC)) + ((1+DISCOUNT)**NYRSPER)$ENU(ENC)))
    +
    SUM(ENC $ (REL_ENC(ENC,TEG) AND ((ORD(TP) + TCH_LIFE(TEG) - CARD(TP)) GT 0)),
      SAL_REL(ENC)
      * (PRC_OUT1(TEG,ENC) + CON_OUT1(TEG,ENC) + DMD_MOTID(TEG,ENC))
      * ((1+DISCOUNT) ** (-NYRSPER * (TCH_LIFE(TEG) + 1$ENU(ENC))))))
* correct salvage credit for technology-based discount rates
   * (1 - (1 + DISCOUNT$(NOT TCH_DISC(TEG)) + TCH_DISC(TEG))
       ** (- NYRSPER * (ORD(TP) + TCH_LIFE(TEG) - CARD(TP) - 1)))
   / ((1 + DISCOUNT$(NOT TCH_DISC(TEG)) + TCH_DISC(TEG))
     ** (NYRSPER * (CARD(TP) + 1 - ORD(TP))))
   / (1 - (1 + DISCOUNT$(NOT TCH_DISC(TEG)) + TCH_DISC(TEG))
       ** (- NYRSPER * TCH_LIFE(TEG)))
  );

%1_SV2(%5TP, %5TEG)$((ORD(TP) + TCH_LIFE(TEG) - CARD(TP)-1) LE 0)..SV_INV(TP, TEG)
 =E= 0;

*$OFFLISTING
```

2. File MMCOEF1.INC

```
*************************************************************************************
*                                              *
*   Parameters technological change            *
*                                              *
*************************************************************************************
PARAMETER PAT(TEG)    / EMPTY 0 /;
PARAMETER SC0(TEG)    / EMPTY 0 /;
PARAMETER PBT(TEG)    / EMPTY 0 /;
PARAMETER PRAT(TEG)   / EMPTY 0 /;
PARAMETER SEG(TEG)    / EMPTY 0 /;
PARAMETER CCAP0(TEG)  / EMPTY 0 /;
PARAMETER CCOST0(TEG) / EMPTY 0 /;
PARAMETER CCOSTM(TEG) / EMPTY 0 /;
PARAMETER CCAPM(TEG)  / EMPTY 0 /;
PARAMETER WEIG(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER CCOSTK(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER CCAPK(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER BETA(KP, TEG) / EMPTY.EMPTY 0 /;
PARAMETER ALPH(KP, TEG) / EMPTY.EMPTY 0 /;

* computation of the learning curve exponent

PBT(TEG)=-LOG(PRAT(TEG))/LOG(2);

* computation of the learning curve coefficient

PAT(TEG)=SC0(TEG)*(CCAP0(TEG)**(PBT(TEG)));
```

```
* assignment of the initial cumulative cost

CCOST0(TEG)=(PAT(TEG)/(1-PBT(TEG)))*(CCAP0(TEG)**(1-PBT(TEG)));

* assignment of the maximum cumulative cost

CCOSTM(TEG)=(PAT(TEG)/(1-PBT(TEG)))*(CCAPM(TEG)**(1-PBT(TEG)));

* assignment of the kink points for cumulative cost

ICOUNT=1;
LOOP(KP$(ORD(KP) GE 2),
WEIG(KP, TEG)=(2**(-SEG(TEG)+ICOUNT-1))/(sum(RP$(ORD(RP) LE (SEG(TEG))), (2**(-
SEG(TEG)+ORD(RP)-1))));
ICOUNT= ICOUNT+1;
);

CCOSTK('0', TEG)=CCOST0(TEG);

ICOUNT=1;
LOOP(KP$(ORD(KP) GE 2),
CCOSTK(KP, TEG)=CCOSTK(KP-1, TEG)+((CCOSTM(TEG)-CCOST0(TEG))*WEIG(KP, TEG));
ICOUNT= ICOUNT+1;
);

* assignment of the kink points for cumulative capacity

CCAPK(KP, TEG)$(ORD(KP) LE SEG(TEG)+1)=(((1-PBT(TEG))/PAT(TEG))*CCOSTK(KP,
TEG))**(1/(1-PBT(TEG)));

* assignment of beta coeff. for interpolation of cumulative cost

BETA(KP, TEG)$(ORD(KP) LE SEG(TEG)+1)= (CCOSTK(KP, TEG)-CCOSTK(KP-1,
TEG))/(CCAPK(KP, TEG)-CCAPK(KP-1, TEG));

* assignment of alpha coeff. for interpolation of cumulative cost

ALPH(KP, TEG)$(ORD(KP) LE SEG(TEG)+1)=CCOSTK(KP-1, TEG) - BETA(KP, TEG)*CCAPK(KP-
1, TEG);

* Set the investment cost of the learning technologies to zero

TCH_INVCOS(TEG, TP)=0;
```

3. File MMVARS1.INC

```
*====================================================*
*  Technological change variables                    *
*====================================================*
POSITIVE VARIABLES

LAMBD(TP, TEG, KP)
```

```
CCAP(TP, TEG)
CCOST(TP, TEG)
IC(TP, TEG)
SV_INV(TP, TEG)

BINARY VARIABLES

DELTA(TP, TEG, KP)
```

4. File MMEQPRI1.INC

```
* Technological change - Capacity for learning technologies
 SUM(TP%8TCH%3(%5TP, %9%2TEG),
  (
  (1 / ((1 + DISCOUNT) ** (- STARTYRS + NYRSPER * (ORD(TP) - 1)))) *
* add fractional lifetime correction multiplier
   CRF_RAT(TEG) * FRACLIFE(TEG) *
  (IC(%5TP, %5TEG) - SV_INV(%5TP, %5TEG)))
 ) +
```

5. File MMEQUA1.INC

5.1 Include the following lines into the EQUATIONS declaration:

```
* MIP formulation of learning curves

 EQ_CUINV(TP, TEG)          Cumulative Capacity Definition
 EQ_CC(TP, TEG)             Cumulative Capacity Interpolation
 EQ_DEL(TP, TEG)            Delta to 1
 EQ_COS(TP, TEG)            Cumulative Cost
 EQ_LA1(TP, TEG, KP)        Logical Conditions 1
 EQ_LA2(TP, TEG, KP)        Logical Conditions 2
 EQ_EXPE1(TP, TEG, KP)      Experience grows 1
 EQ_EXPE2(TP, TEG, KP)      Experience grows 2
 EQ_IC1(TP, TEG)            Investments tech. change starting period
 EQ_IC2(TP, TEG)            Investments tech. change other periods
 EQ_SV(TP, TEG)             Salvage on investments
 EQ_SV2(TP, TEG)            Additional condition for salvage
```

5.2 Make the following change to call the file with the modified objective function:

```
*============================================*
* Total Discounted System Cost               *
*============================================*
$BATINCLUDE MMEQPRI1.INC EQ '' '' '' '' '' '' '' '' '' '' 'E'
```

5.3 Call the file with the technological change equations:

```
*===== ============================*
*   Technological change equations  *
*                                   *
*================== ===============*
$BATINCLUDE MMEQTEG1.INC  EQ '' '' '' '' '' '' ''
```

6. File MODEL1.MRK

Include the following list of equations into the MODEL declaration

```
* Technological Change
  EQ_CUINV
  EQ_CC
  EQ_DEL
  EQ_COS
  EQ_LA1
  EQ_LA2
  EQ_IC1
  EQ_IC2
  EQ_EXPE1
  EQ_EXPE2
  EQ_SV
  EQ_SV2
```

7. File MMINIT1.INC

```
*Technological change
    SET TEG(TCH) / EMPTY /;
```

8. File MMSETS1.INC

```
* Set of learning technologies

SETS TPTEG;

TPTEG(TP,TEG) = TPTCH(TP,TEG);
```

Declare an Alias of set KP

```
ALIAS(KP, RP);
```

9. File SOLVE1.MRK

```
* main solve for MARKAL
$IF NOT '%RUN_MREG%' == 'YES'  SOLVE MRK MINIMIZING OBJZ USING MIP;
```

10. File MMINCLU1.INC

Change the names of included files where required to use the new formulation:

```
$ INCLUDE MMSETS1.INC
$ INCLUDE MMCOEF1.INC
$ INCLUDE MMVARS1.INC
$ INCLUDE MMEQUA1.INC
$ INCLUDE MODEL1.MRK

* solve MRK if MARKAL or MM with PRESOLVE run
```

```
$ IF %3 == 'PRESOLVE' $ BATINCLUDE SOLVE1.MRK %3
 IF (MODE = 1,
$   BATINCLUDE SOLVE1.MRK %3
 );
```

11. File XXXXX.GEN

Include the following in your *.gen file

```
OPTION MIP=CPLEX; or OSL
```

Declare and define set KP (KP is an ordered set and has to be declared at the very beginning, that is, even before calling MMINIT1.INC)

```
SET KP      / 0*6 /;

$ INCLUDE MMINIT1.INC
$BATINCLUDE MMINCLU1.INC GMARKAL START SOLVE
```

12. File XXXXX.DD

SETS

```
SET  TEG(TCH) 'ENDOGENOUS TECH. CHANGE'
/
E61     'WIND TURBINE              '
E41     'SOLAR PHOTOVOLTAICS       '
/
```

PARAMETERS

```
SEG(TCH) number of segments per technology
/ E61  6
  E41  5    /

 SC0(TCH)
/ E61           800.
  E41           5000. /

PRAT(TCH)
/ E61           0.85
  E41           0.85 /

CCAP0(TCH)
/ E61           5.0
  E41           0.5 /

CCAPM(TCH)
/ E61           3000.
  E41           3000 /
```