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RR-04-010
November 2004

REPRINT
RESEARCH
REPORT

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Reprinted from *Technovation*, **24**(8):615-629 (2004).

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Endogenizing R&D and market experience in the "bottom-up" energy-systems ERIS model

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Abstract

ERIS, an energy-systems optimization model that endogenizes learning curves, is modified in order to incorporate the effects of R&D investments, an important contributing factor to the technological progress of a given technology. For such purpose a modified version of the standard learning curve formulation is applied, where the investment costs of the technologies depend both on cumulative capacity and the so-called knowledge stock. The knowledge stock is a function of R&D expenditures that takes into account depreciation and lags in the knowledge accumulated through R&D. An endogenous specification of the R&D expenditures per technology allows the model to perform an optimal allocation of R&D funds among competing technologies. The formulation is described, illustrative results presented, some insights are derived, and further research needs are identified.

Keywords: Learning curves; R&D; Market experience; Energy-systems models

1. Introduction

Research and development (R&D) is one of the basic driving forces of technological progress, contributing to productivity increases and economic growth. Although difficult to measure, the payoffs produced by R&D expenditures are high, both at social and private levels (Griliches, 1995). R&D is also one of the variables that government policies may affect, as private companies are likely to not invest enough in R&D from a public interest perspective, particularly in technologies that are promising only in the long run.

In the case of energy systems, R&D constitutes a fundamental factor for the successful introduction of new, more efficient and clean supply and end-use technologies and the achievement of economic, safety, environmental and other goals. Therefore, it is important to study the main mechanisms by which R&D investments contribute to cost and performance improvements of individual technologies and productivity increases of the energy system as a whole. By the same token, it is also interesting to gain insights about the optimal allocation of scarce R&D resources, taking into account that such allocation is influenced by expectations of market opportunities. Thus, it becomes necessary to incorporate those mechanisms into the energy policy decision-support frameworks, e.g., in energy-systems optimization models.

However, assessing and quantifying the effects of R&D efforts in energy technology innovation is particularly difficult because of a number of reasons, the broad range of R&D activities relevant to energy issues, the variety of institutions carrying R&D, the difficulties in assessing the (central) role played by industrial R&D and the lack of underlying data, among others (see, e.g., Sagar and Holdren, 2002 for a discussion). Moreover, the role of R&D must be examined within the context of the whole energy innovation system, of which R&D activities are only a part. Demonstration and deployment of energy technologies in the marketplace also play a very important role in their improvement, in particular regarding cost reductions (Grübler, 1998; PCAST, 1999; IEA, 2000, among others).

Technological learning plays an important role in technological change. Learning has many different sources, such as production (learning-by-doing), usage (learning-by-using), R&D efforts (learning-by-searching) and interaction between different social actors

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0166-4972/$ - see front matter © 2002 Elsevier Ltd. All rights reserved.
doi:10.1016/S0166-4972(02)00124-4

(learning-by-interacting), among others (Grübler, 1998). There are a number of technical, social, economical, environmental and organizational factors that influence the presence (or absence) and rate of technological learning processes.

The typical representation of this phenomenon is through learning, or experience, curves. The standard learning curve considers the specific investment cost of a given technology as a function of cumulative capacity or cumulative production, which is used as an approximation for the experience accumulated when the technology is deployed. The formulation reflects the fact that some technologies experience declining costs as a result of their increasing adoption (Argote and Epple, 1990). As such, it takes into account the effects of experience due to actual deployment of technologies but it does not provide a mechanism to capture explicitly the effects of public and private R&D efforts, which also constitute an essential component of cost reductions and performance improvements, particularly in the early stages of development of a technology.

There is a need to incorporate R&D activities within the technological learning conceptual framework. R&D and market experience can be thought of as two learning mechanisms that act as complementary channels for knowledge and experience accumulation (Goulder and Mathai, 2000). Both mechanisms play an important role. R&D is critical at early stages of development and to respond to market needs, but market experience is essential to achieve competitiveness. There are also feedbacks between these two learning mechanisms. Successful R&D may increase the possibilities of a particular technology to diffuse. Market experience, on the other hand, may contribute to increment the effectiveness of R&D efforts, helping to target them towards needs identified when manufacturing and using the technology.

Examples of this interaction have been described in the literature. Neij (1999) and Loiter and Norberg-Bohm (1999), for instance, discuss the case of wind turbines. As a rule, experience gained with deployment of capacity seems to have been critical for progress in wind turbines, having also an influence in the effectiveness of R&D efforts. R&D programs seem to have been more successful when addressing specific problems made evident by the operation experience (Loiter and Norberg-Bohm, 1999). Having a market where new R&D results could be tested was an important feedback mechanism for research and focusing on concrete challenges allowed a more agile and wide incorporation of the innovations produced in such programs in subsequent generations of the technology. Watanabe (1999) performed an analysis of the role of public and private R&D expenses and industrial production in the competitiveness of solar photovoltaics in Japan and, on such basis, they identified the existence of a "virtual cycle" or positive feedback loop between R&D, market growth and price reduction which stimulated its development.

Thus, a comprehensive view of technological learning processes and associated policy measures must encompass Research, Development, Demonstration and Deployment (RD3) activities (PCAST, 1999), since all of them play a role in stimulating energy innovation and in the successful diffusion of emerging energy technologies. Energy technology RD3 strategies require, among other actions, a combination of "technology push" and "demand pull" policy measures.

On the "technology push" side, well-defined technology roadmaps and strategic R&D portfolios that conciliate short-term and long-term needs may contribute to make technologies available that could enable the provision of energy services in a cleaner, more flexible and reliable way and that can respond to objectives such as climate change mitigation and sustainability. On the "demand pull" side, buy-down policies, procurement and market transformation programs, for instance, could support cleaner and more efficient energy supply and demand technologies, which are currently expensive but with a promising learning potential (Payne et al., 2001; Neij, 2001; Olerup, 2001). Such policies could contribute to finance the "learning investments" (also called maturation costs), i.e., the investments necessary for these technologies to move along their learning curves until they become competitive.

However, R&D productivity is difficult to measure, not least because the observable variables can provide only a partial view of the innovation process. R&D expenditures are used as one of the typical measures of R&D activity. However, there are obstacles in establishing cause/effects relationships between R&D expenditures and technological progress, since R&D expenditures measure an input to the innovation process and not its output(s). In addition, even gathering R&D expenditures can be difficult, particularly for industrial R&D activities.

In addition, sound models for the role of R&D in the energy innovation system are not yet available. Clearly, because of the multiple feedbacks between the different factors, a linear model of innovation cannot be established (i.e., with R&D exclusively preceding market experience). However, there is a need for defining, if possible, basic stylized causal rules of interaction between R&D and market experience and their respective effects on technological progress, e.g., cost reductions and/or performance improvements. Regarding the latter, one of the difficulties is that R&D results may not necessarily contribute to the progress of a single technology but to that of several products or services.

Different approaches to model the R&D factor as an endogenous driver of technological change in "top-down" and "bottom-up" models have been reported in the literature (see e.g., Grübler and Gritsevskyi, 1997;

Kouvaritakis et al., 2000a; 2000b; Goulder and Mathai, 2000; Buonanno et al., 2000). In "top-down" models, such as the one presented by Buonanno et al. (2000), the representation is normally through a general knowledge stock that depends on R&D expenditures and is incorporated as a production factor in the production function. Such knowledge stock affects productivity and emission coefficients.

In "bottom-up" approaches, the different formulations try to establish a link between these two factors and cost reductions of individual technologies. For such purpose, modifications of the standard learning curve have been proposed. Grübler and Gritsevskyi (1997) present a stochastic optimization micro model, which incorporates uncertain returns on learning due to both R&D and market investments. For that purpose a modified learning curve is used. Such a curve considers cumulative expenditures instead of cumulative capacity as the proxy for accumulation of knowledge. Expenditures in both R&D and commercial capacity deployment are added up to contribute to the cumulative expenditures. Such an approach considers the two factors as complementary and it has the advantage of measuring both factors in common (monetary) units. However, it does not allow for differentiating their contributions. That is, one monetary unit of R&D produces the same effect as one of cumulative market investments.

Kouvaritakis et al. (2000a; 2000b) have applied the so-called two-factor learning curve (hereon referred to as 2FLC) concept in POLES, a system dynamic, behavioral-oriented model where technological learning is driven by adaptive expectations (i.e., without perfect foresight). The 2FLC is an extension of the standard learning curve, which is based on the hypothesis that cumulative capacity and cumulative R&D expenditures drive the cost reductions of the technology. In such 2FLC formulation, the specific cost of a given technology is a function of cumulative capacity and cumulative R&D expenditures. Such a function is assumed to be of the same kind of a Cobb–Douglas production function, with both factors acting as substitutes according to their corresponding so-called learning-by-doing and learning-by-searching elasticities.

The ERIS (Energy Research and Investment Strategy) model was developed as a joint effort between several partners within the EC-TEEM project.[1] ERIS is a perfect-foresight energy-systems optimization model. It provides a stylized representation of the global electricity generation system and endogenizes learning, or experience, curves. The original specification was made by Messner (1998) and implemented by Capros et al. (1998); Kypreos (1998) and Kypreos and Barreto (1998). A detailed description of the model may be found in Kypreos et al. (2000). Analyses using ERIS have been reported in Barreto and Kypreos (2000).

Here, a modified version of the 2FLC, which incorporates the concept of knowledge stock instead of cumulative R&D expenditures, is implemented in ERIS. In doing so, we recognize the limitations posed by the 2FLC hypothesis and the unsolved estimation and data issues associated with it, but emphasize the fact that it constitutes an important step towards the understanding of the role of R&D in energy innovation and its conceptual treatment in energy systems models and the fact that the work has helped to identify a number of research needs in this area. Additional analyses applying the formulation of ERIS with 2FLC developed here are presented by Miketa and Schrattenholzer (2001).

The remainder of this paper is structured as follows. First, the standard formulation of learning curves incorporated in ERIS is briefly described in Sect. 2, in order to provide a reference for the developments presented here. Then, the concept of knowledge stock is introduced in Sect. 3. Subsequently, the implementation of the 2FLC in ERIS is presented in Sect. 4. Sections 5 to 7 present and discuss some illustrative examples. Finally, some concluding observations and research needs are outlined in Sect. 8.

2. The original single-factor learning curve formulation in ERIS

In the standard formulation of the experience curve, the specific investment cost ($SC_{te,t}$) of a given technology, te, in time period, t, is defined as a power function of its cumulative capacity (Argote and Epple, 1990):

$$SC_{te,t}(C) = a * C_{te,t}^{-b_{te}}$$

with $C_{te,t}$: Cumulative capacity, b: Learning index, a: Specific cost at unitary cumulative capacity.

The coefficient, a, can be computed with the initial point ($SC_{te,t}$, $dcap_{te,t}$) of the learning curve. Using ERIS notation it can be expressed as:

$$a = SC_{te,0}/(dcap_{te})^{-b_{te}} = i_{te,rg} * (dcap_{te})^{b_{te}}$$

with: $SC_{te,0}$ Initial specific investment cost (\$/kW), $dcap_{te}$ Initial cumulative capacity (GW), $i_{te,rg}$ Specific investment cost of the technology, te (\$/kW).

The learning index, b, defines the effectiveness with which the learning process takes place. It constitutes one of the key parameters in the expression above. Usually, its value is not given but the learning rate is specified instead. The learning rate (LR) is the rate at which the cost declines each time the cumulative production doubles. For instance, a learning rate of 20% implies that

[1] Energy Technology Dynamics and Advanced Energy System Modelling. Project of the Non-nuclear Energy Programme Joule III — European Commission (TEEM, 1999).

the costs are reduced 20% from their previous value when the cumulative capacity is doubled. The relation between the learning rate and the learning index can be expressed as:

$$LR = 1-2^{-b}.$$

The cumulative capacity of a given technology, te, in the time period, t, corresponds to the summation of the past investments (in physical units) up to time, t, plus the initial cumulative capacity that defines the starting point on the experience curve ($dcap_{te}$). The cumulative capacity ($C_{te,t}$) is a non-decreasing variable. In ERIS, $C_{te,t}$ is expressed as the product of the growth relative to the initial cumulative capacity ($G_{te,t}$) and the initial cumulative capacity ($dcap_{te}$). If it is assumed that capacity is accumulated across all regions, this expression takes the form:

$$C_{te,t} = G_{te,t}*dcap_{te} = dcap_{te} + \sum_{rg}\sum_{\tau=1}^{t} I_{te,\tau,rg}*\Delta_\tau$$

where: $I_{te,t,rg}$ Annual investments on technology te in period t-1 in the region rg (GW), $G_{te,t}$ Global growth factor – relative to $dcap_{te}$ – for a given technology up to period t, Δ_τ: Length of the period.

The expression for the specific cost given above is not applied directly in the model but the cumulative cost curve is used instead. The cumulative cost ($TC_{te,t}$) as a function of the cumulative capacity ($C_{te,t}$) is the integral of the specific cost curve with respect to $C_{te,t}$:

$$TC_{te,t} = \int_0^C SC(C)*dC = \frac{a}{1-b}C_{te}^{1-b_{te}}$$

$$= \frac{i_{te,rg}}{1-b_{te}}(G_{te,t})^{1-b_{te}}*dcap_{te}.$$

The investment costs per period for a given technology ($ICOST_{te,t}$) are computed as the subtraction of two consecutive values of $TC_{te,t}$:

$$ICOST_{te,t} = TC_{te,t}-TC_{te,t-1} = \frac{i_{te,rg}}{1-b_{te}}*dcap_{te}*[(G_{te,t})^{1-b_{te}} -(G_{te,t-1})^{1-b_{te}}].$$

The NLP formulation of ERIS uses the right-hand side of the above expression directly embedded in the objective function, which in this case corresponds to the total discounted system costs. When this expression is incorporated in the objective function of the model, the optimization problem becomes non-linear and non-convex. Such kinds of problems exhibit multiple locally optimal solutions. Conventional non-linear programming (NLP) algorithms can only guarantee the identification of a local optimum.

An alternative formulation of ERIS provides a linearization of the problem applying Mixed Integer Programming (MIP) techniques. The MIP approach uses a piecewise interpolation of the cumulative cost curve where integer variables are introduced to control the sequence of segments along the curve. Although computationally intensive, the MIP formulation allows the identification of a unique optimal solution for the approximated problem. For a detailed description of both formulations in ERIS see Kypreos et al. (2000).

3. The knowledge stock function

An important issue concerns the variable used to represent the knowledge accumulated through R&D efforts. In this section we describe the main characteristics of the knowledge stock function applied here.

As mentioned above, Kouvaritakis et al. (2000a; 2000b) have used cumulative R&D expenditures as the representative variable, where past R&D expenditures are added up in a similar way as past investments are when computing the cumulative capacity. The cumulative R&D expenditures ($CRD_{te,t}$) can be defined as:

$$CRD_{te,t} = dcrd_{te} + \sum_{\tau=1}^{t} ARD_{te,\tau}*\Delta_\tau$$

where: $dcrd_{te}$: Initial cumulative R&D expenditures per technology, te, $ARD_{te,t}$: Annual R&D expenditures per technology, te, and period, t, Δ_τ: length of the period.

A more complete representation of the knowledge accumulated through R&D efforts can be obtained with a knowledge stock function, as proposed in the literature (Griliches, 1984, 1995; Watanabe, 1995, 1999). The knowledge stock allows for taking into account several aspects of the R&D process. On the one hand, it takes time to conduct R&D projects as well as to apply the results to the production process. Thus, there are time lags between the actual R&D expenditures and the corresponding effects on productivity. On the other hand, past R&D investments depreciate and become obsolete (Griliches, 1995). In order to capture those characteristics, a general knowledge stock function can be formulated in terms of current and past R&D expenditures, which may depreciate in time.

Here, the recursive expression for knowledge stock proposed by Watanabe (1995, 1999) is implemented. Such formulation assumes that knowledge depreciates in time at a constant rate δ and that only the R&D expenditures performed n years before contribute to the current knowledge stock. That is, a constant lag is assumed between the time at which R&D spending takes place and the time at which its results materialize and become part of the knowledge stock. The original expression is given on a year-by-year basis. The knowledge stock in the year y (K_y) is expressed as the summation of the (depreciated) stock of the previous year (K_{y-1}) and the lagged R&D expenditures ($ARD_{y-rdlag}$):

$$K_y = (1-\delta)*K_{y-1} + ARD_{y-rdlag}$$

where: K_y: Knowledge stock in year y, K_{y-1}: Knowledge stock in year y − 1, δ: Annual depreciation rate, $ARD_{y-rdlag}$: Lagged annual R&D expenditures per technology, rdlag: Lag in years between R&D expenditures and knowledge stock.

The above is an annual expression but in ERIS values are assigned to variables on a period-by-period basis and the length of the period is normally bigger than one year. Therefore, in order to be consistent, it is necessary to compute the knowledge stock for each period in the model, taking into account the year-by-year formulation above. For such purpose, it is assumed that annual R&D expenditures per technology are constant along the period, as it is the case with the other variables in the model. The value of the knowledge stock for a given period (computed at the end of the period) is obtained using the corresponding ARD series for the current and the previous periods as:

$$K_t = K_{t-1}*(1-\delta)^{\Delta_t} + ARD_t* \sum_{\tau=0}^{\Delta_t-rdlag-1} (1-\delta)^\tau + (1-\delta)^{\Delta_t-rdlag}*ARD_{t-1}* \sum_{\tau=0}^{rdlag-1} (1-\delta)^\tau.$$

This expression provides a period-by-period computation of the knowledge stock that is consistent with the above year-by-year formulation, under the assumption that the R&D expenditures series remains constant along each period.

For the first period the computation must include the lagged historical annual R&D expenditures values ($ardpast_\tau$) and thus it becomes:

$$K_t = dknow*(1-\delta)^{\Delta_t} + ARD_t* \sum_{\tau=0}^{\Delta_t-rdlag-1} (1-\delta)^\tau + (1-\delta)^{\Delta_t-rdlag}*[\sum_{\tau=0}^{rdlag-1} (1-\delta)^\tau*ardpast_\tau]$$

where the $ardpast_\tau$ values are given backwards with respect to the specification of the initial knowledge stock (*dknow*). That is, $ardpast_0$ corresponds to the R&D expenditures in the same year for which *dknow* is given, $ardpast_1$ are those of the previous year, etc. The equations above assume that *rdlag* < period length (Δ_t).

The computation is performed at the end of each period because the cumulative capacity for a given period is computed as the one in the previous period plus the investments taking place in the current one, and both values should be consistent in order to be introduced into the learning curve.[2]

The knowledge stock appears to be a more suitable form of measuring the R&D contribution than simply cumulating R&D expenditures on time. Of course, when no depreciation or lags are considered, it reduces to cumulative R&D expenditures. However, the knowledge stock also introduces the problem of obtaining sensible assumptions or estimations of the relevant lag structure and the depreciation rate. Although some case studies are available (Watanabe, 1999), estimates of such parameters in the case of energy technologies are still to be developed.

In view of the uncertainty associated with empirical estimates of the learning-by-doing, learning-by-searching, depreciation and time lags for energy technologies, sensitivity analyses are necessary to establish which of the models is the more responsive. Those analyses may be also useful to examine the effects of different assumptions on the relative competitiveness of the different technologies. For such task, ERIS may constitute a valuable tool.

4. The two-factor learning curve formulation in ERIS

Applying the definition of knowledge stock described above, the 2FLC for the specific investment costs of a given technology can be expressed as:

$$SC_{te,t} = a*C_{te,t}^{-b}*KS_{te,t}^{-c}$$

where: $C_{te,t}$: Cumulative capacity, $KS_{te,t}$: Knowledge stock, b: Learning by doing index, c: Learning by searching index, a: Specific cost at unit cumulative capacity and unit knowledge stock.

Instead of the learning-by-doing and learning-by-searching indexes, corresponding learning-by-doing (LDR) and learning-by-searching (LSR) rates can be defined as follows:

$$LDR = 1-2^{-b},$$

$$LSR = 1-2^{-c}.$$

It must be noticed that the LDR does not correspond to the LR described above for the single-factor learning curve. In the 2FLC, two variables, namely the cumulative capacity and the knowledge stock, are used to expli-

[2] In ERIS, it is assumed that the period named as "2000" comprises the years from 2001 to 2010, the period "2010" goes from 2011–2020, etc. Thus, for the purposes of knowledge stock calculation the variable ARD(2000) will be the annual R&D expenditures for 2001–2010 and the variable KNOW(2000) is the corresponding knowledge stock at the end of the period.

cate the cost trend that the 1FLC tries to capture using only cumulative capacity as explanatory variable.

As mentioned above, this is a hypothetical formulation for which solid empirical support is still to be gathered. This formulation assumes that the two factors can be used interchangeably to produce cost reductions in a given technology once it is available in the market and that, if the LSR is positive (when using the convention applied here), increasing R&D expenditures in a given technology will contribute to reduce its investment cost. Here, we do not address the characteristics of the technology's learning process before the commercialization stage is reached or postulate that the 2FLC aggregate model is valid for such a stage.

The inclusion of the knowledge stock in the learning curve provides the model with a mechanism of "forgetting-by-not-doing" for the R&D learning channel. That is, leaving aside the effects of cumulative capacity, if no R&D expenditures are made in a given technology, the knowledge stock will depreciate. Consequently, the specific costs of the technology will increase. It would be interesting to examine whether a similar mechanism should be incorporated also in the cumulative capacity learning channel.

Notice also that with this formulation, if both learning-by-doing and learning-by-searching indexes were equal, in principle investing in capacity deployment rather than in R&D would be the preferred option in the model because when investing in capacity not only is the cost reduced but the capacity becomes available to produce energy, while the benefits of effecting R&D investments are restricted to the cost reduction (Criqui et al., 2000).

As above, this expression is not applied directly in the model formulation, but the cumulative cost curve is used instead. Thus, the changes are applied to the latter one. We will describe the 2FLC formulation in ERIS following the description made above for the standard single-factor learning curve formulation. In such a way, the differences may more easily become apparent to the reader.

Using the initial point of the standard learning curve (SC_0, $dcap_{te,t}$) plus the initial value of the knowledge stock per technology ($dknow_{te}$), the coefficient a can be now expressed as:

$$a = SC_{0,te}/[(dcap_{te})^{-b}*(dknow_{te})^{-c}]$$
$$= i_{te,rg}*(dcap_{te})^{b}*(dknow_{te})^{c}.$$

The cumulative cost ($TC_{te,t}$) can be expressed as the integral of the specific cost curve with respect to $C_{te,t}$.

$$TC_{te,t} = \int_0^C SC(C,KS)*dC = \frac{a}{1-b}C_{te,t}^{1-b_{te}}*KS_{te,t}^{-c_{te}}.$$

Then:

$$TC_{te,t} = \int_0^C SC(C,KS)*dC =$$
$$= \frac{i_{te,rg}*dcap_{te}*(dknow_{te})^c}{1-b_{te}}*(G_{te,t})^{1-b_{te}}*(KS_{te,t})^{-c_{te}}.$$

Thus, the undiscounted investment cost ($ICOST_{te,t}$), computed as the difference between two consecutive cumulative cost values, becomes:

$$ICOST_{te,t} = TC_{te,t}-TC_{te,t-1}$$
$$= \frac{i_{te,rg}}{1-b_{te}}*dcap_{te}*(dknow_{te})^c*[(G_{te,t})^{1-b_{te}}*(KS_{te,t})^{-c_{te}}$$
$$-(G_{te,t-1})^{1-b_{te}}*(KS_{te,t-1})^{-c_{te}}].$$

Due to the form of the term $(KS_{te,t})^{-c}$, which now multiplies the cumulative cost, this formulation does not intrinsically ensure that $TC_{te,t}$ values remain non-decreasing. Therefore, in principle the values of $ICOST_{te,t}$ could become negative if the R&D component produces a too-steep decrease of the specific cost. Thus, additional checking is required to ensure that consistent values are obtained.

The R&D expenditures per technology and time period ($ARD_{te,t}$) can be given exogenously or can be determined endogenously by the model. Here the endogenous case is examined. That is, $ARD_{te,t}$ and $KS_{te,t}$ are declared as variables. Letting the model choose which fraction of a given R&D budget should each of the competing learning technologies become, it can act as a decision-support tool regarding the adequate allocation of R&D funds across a portfolio of competing technologies.

An annual R&D budget is specified (GRD_t), which can be allocated among the different learning technologies. The R&D budget constraint is formulated as an inequality. With such specification, the model can decide whether the assigned R&D budget should be spent or not, that is:

$$GRD_t \geq \sum_{te \in TEG} ARD_{te,t}$$

TEG: Set of learning technologies.

For a multi-regional model GRD_t can be expressed as the summation of regional budgets:[3]

$$GRD_t = \sum_{rg} GRD_{rg,t}.$$

The objective function is modified in order to include the R&D investments. The new objective function becomes:

[3] The regions belonging to a given spatial learning domain. All of them if global learning is assumed.

$$z' = z + \sum_{t=1}^{T} \sum_{te \in TEG} ARD_{te,t} * (1+d)^{-\Delta_t * t} * \Delta_t$$

with: z′: Total discounted system costs including discounted R&D expenditures, z: Total discounted system costs without R&D expenditures, d: Discount rate.

If required, additional maximum and minimum growth constraints can be specified for the $ARD_{te,t}$ as follows:

$$ARD_{te,t} \leq ARD_{te,t-1} * (1 + grrd)^{\Delta_t},$$

$$ARD_{te,t} \geq ARD_{te,t-1} * (1 - derd)^{\Delta_t}$$

where: grrd: Maximum annual growth rate for R&D expenditures, derd: Maximum annual decline rate for R&D expenditures.

This formulation with endogenous R&D expenditures was applied only to the NLP version of the model. Its direct inclusion in the MIP formulation would produce a NLMIP problem and was not attempted here.

Due to the non-linear, non-convex nature of the problem, solving the NLP version with conventional solvers such as MINOS5, the one used here, enables only the identification of a locally optimal solution. In fact, even if the solution found with the standard NLP algorithm corresponds to the global optimum, it cannot be identified as such. However, previous experiments (Kypreos and Barreto, 1998) with the single-factor formulation of the learning curve have shown that if the solution of the MIP problem is used as a starting point for the NLP problem, in some cases it is possible to identify a better local optimum. A similar procedure is followed here for the 2FLC NLP problem. The solution of the single-factor MIP problem is used as the starting point of the two-factor NLP problem with endogenous R&D expenditures. Such a solution to the restarted NLP problem is the one reported here.

The caveat should be made that there is no guarantee that such a procedure is the most adequate for the two-factor NLP problem. It is possible that using the single-factor MIP solution as a starting point, the model will find a two-factor NLP solution in the "vicinity" of the single-factor learning curve MIP solution, which is not necessarily the best possible alternative. The reader should be aware that, since only a conventional NLP solver is used here, we do not claim that the procedure applied allows the identification of the global optimum for the 2FLC problem. Therefore, we limit ourselves to examine the behavior of the model for the local optimum identified the conventional NLP solver MINOS5. The issue should be explored more carefully in the future and alternatives such as the application of global optimization algorithms (see, e.g., Manne and Barreto, 2001) should be considered.

5. Description of the test case

In this section some results of applying the 2FLC formulation described above are presented. As a test case, the multi-regional ERIS model of global electricity generation applied in Barreto and Kypreos (2000) is considered here. The model divides the world into nine geopolitical regions. Four regions represent the industrialized 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 and Former Soviet Union (EEFSU). Together, the five regions conform to the so-called Annex B group of the Kyoto protocol. Four additional regions group together the developing countries: China (CHINA), India (INDIA), Mexico and OPEC (MOPEC), and the Rest of the World (ROW). They conform to the non-Annex B group. For convenience results are presented here only at the global aggregate level.

As an illustrative example we have chosen a case where the global electricity system must fulfill a Kyoto-for-ever constraint. That is, Annex B regions must achieve their Kyoto targets by 2010 and keep such levels of CO_2 emissions constant along the rest of the time horizon. Emissions in non-Annex B regions are constrained only to their baseline values. Emission trading between Annex B regions is allowed from 2010. After 2030 non-Annex B regions join the CO_2 trading system. A 5% discount rate is used in all calculations. The time horizon of this exercise is 2000–2050.

Technology representation is relatively detailed. Thirteen different electricity generation technologies are considered in the model (see Table 1). Their characteristics are assumed equal across regions. Six technologies are considered to exhibit learning effects. For the other technologies investment costs are assumed constant along the time horizon (i.e., they are considered with effective LDR and LSR of 0%). The corresponding LDR and LSR assumed here are presented in Table 1.

The learning process is considered to occur at the global scale. That is, cumulative capacities are added up across all world regions and R&D expenditures contribute to a global knowledge stock. Thus, both factors contribute to a cost reduction that is common to all regions. That is, full global spillovers of learning are assumed.

Due to the lack of available estimates of two-factor learning curves using knowledge stock for energy technologies[4], additional assumptions were necessary here. The lbd and lbs progress ratios are assumed to be the same as the ones estimated with the cumulative R&D

[4] Some preliminary estimates of two-factor learning curves using knowledge stock for solar PV and wind turbines have been presented in Criqui et al. (2000).

Table 1
Main characteristics of electricity generation technologies considered here

Technology	Abbrev.	Inv. Cost (US$/kW)	Fixed O&M (US$/kW/year)	Var. O&M (US$/kWyr)	LDR	LSR
Conventional Coal	HCC	1357	69	22.7	0	0
Advanced Coal	HCA	1584	67.5	23.6	0.11	0.05
Gas Steam	GSC	987	50.6	17.7	0	0
Gas CC	GCC	600	36.6	19.7	0.24	0.02
Gas Turbine	GTC	350	58.5	16.03	0	0
Gas Fuel Cell	GFC	2463	43.5	80.	0.19	0.11
Oil Steam	OLC	1575	63.6	18.13	0	0
Nuclear	NUC	3075	114	5.91	0	0
New Nuclear	NNU	3400	114	5.91	0.04	0.02
Hydro	HYD	3562	49.5	3.9	0	0
Solar PV	SPV	5000	9.	39.4	0.25	0.10
Wind	WND	1035	13.5	26.3	0.16	0.07
Geothermal	GEO	3075	7.8	92	0	0

expenditures formulation. Those coefficients have been taken from the statistical estimation performed by Kouvaritakis et al. (2000a; 2000b) using cumulative capacity and cumulative R&D expenditures as explicative variables. Also, as a simplification, the initial knowledge stock (*dknow*) for each technology is considered equal to the initial cumulative R&D expenditures (see Table 2 below). In addition, no R&D lag was assumed and the same depreciation rate is applied to all learning technologies. Thus, the results presented here only intend to illustrate the response of the model with this relationship.

As for the R&D expenditures, the figures applied are based on the estimates available from IEPE (2000). The numbers correspond mainly to the aggregation of expenditures in OECD countries, where the bulk of research activities take place. Those figures, however, cannot be considered definitive and they are used here only for illustrative purposes. As mentioned above, there exists significant difficulties in gathering R&D-related information. This is particularly so for business R&D because private manufacturers may not be willing to make their figures publicly available.

The initial cumulative R&D expenditures for each technology corresponds to the summation of the estimates of cumulative governmental and business R&D in 1997, the last year available in the database (see Table 2, figures are in US$ millions as of 1998). In addition, in order to set an initial condition, it is assumed that the annual R&D expenditures ($ARD_{te,t}$) for the first period modeled are also those of 1997.

The illustrative scenario presented here assumes that the available R&D budget increases in the future for this set of technologies. The R&D budget is assumed to increase at 1.5% per year along the time horizon, from a starting value computed as the summation of the expenditures in the six learning technologies for the first period. In addition, a maximum growth rate of 10% per annum and a maximum decline rate of 15% per annum have been specified for all the $ARD_{te,t}$ variables.

6. Some results

In this section, we present some illustrative results obtained with our test case applying the 2FLC formulation described above. We will describe first a situation without depreciation or R&D lags. In Sect. 6, the sensi-

Table 2
Annual and cumulative R&D expenditures for 1997 used as the base for the model assumptions. Figures in US$ millions as of 1998

Technology	Annual Gov. R&D	Annual Business R&D	Annual Total R&D	Cum. Gov. R&D	Cum. Business R&D	Cum. Total R&D
NNU	749	24	773	22927	2244	25171
HCA	116	104	220	5411	3983	9394
GCC	69	1062	1131	1755	25771	27526
WND	143	266	409	2489	4361	6850
GFC	86	294	380	1406	6669	8075
SPV	211	198	409	3803	11091	14894
Total	1374	1948	3322			

tivity to the depreciation rate is examined. When describing the results, we will concentrate mainly on the allocation of the R&D expenditures.

Before describing the results, it is important to notice the way the endogenized learning mechanism acts in the model. Due to the underlying increasing returns mechanism, the model tends to act in an "all-or-nothing" fashion. If a given technology has enough "learning potential" (which depends on the learning rate, starting point of the learning curve, maximum growth rates allowed, upper bounds imposed, etc.), the model will try to install it at the maximum rate possible to exhaust such potential. If not, it will very likely leave it "locked-out".

Fig. 1 presents the global electricity generation for the year 2050 for our test case. With a carbon constraint imposed on the Annex B regions, a significant decarbonization takes place in the global electricity generation system. Coal-fired power plants (HCC, HCA) still hold an important share of the generation mix, with a significant fraction of the coal-fired generation supplied by advanced clean coal technologies. However, the generation mix is dominated by less-carbon-intensive technologies. Gas combined-cycle turbines (GCC) provide the largest contribution. Other technologies, such as solar photovoltaic (SPV), wind turbines (WND) and gas fuel cells (GFC) also have a sizeable share of the market.

The budget is not fully allocated along the time horizon (see Fig. 4 below). In the first period, the full R&D budget is allocated because of the initial condition imposed, as mentioned above. The amount of spent R&D funds decays in the second period, declining to the minimum bound imposed by the minimum growth constraints of the R&D expenditures per technology, which do not allow R&D investments for a particular technology in a given period to be reduced below 20% of the R&D expenditures of the previous period. Afterwards, total R&D expenditures show an upward trend. In the final period, total R&D expenditures decay again. This is mainly due to end effects of the model, as no "salvage costs" for R&D investments have been considered here.

Fig. 2 presents the R&D expenditures per technology and Fig. 3 shows their relative allocation under these

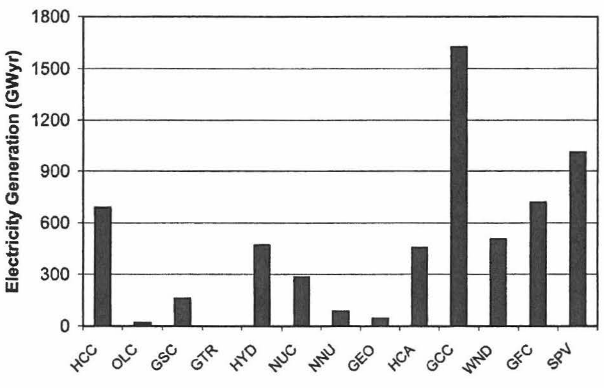

Fig. 1. Global electricity generation mix in the year 2050 in our test case.

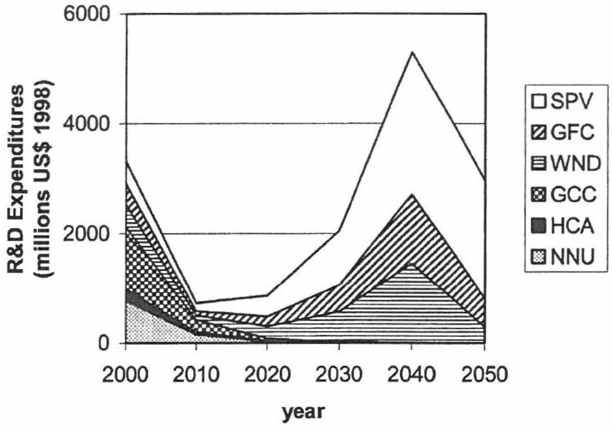

Fig. 2. Annual R&D expenditures per technology in our test case.

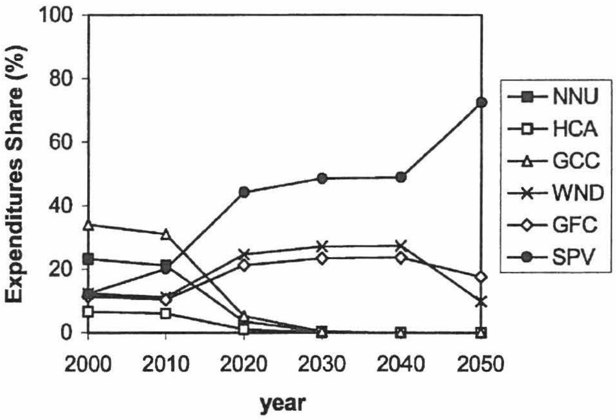

Fig. 3. Share of the total annual R&D expenditures allocated to each learning technology in our test case.

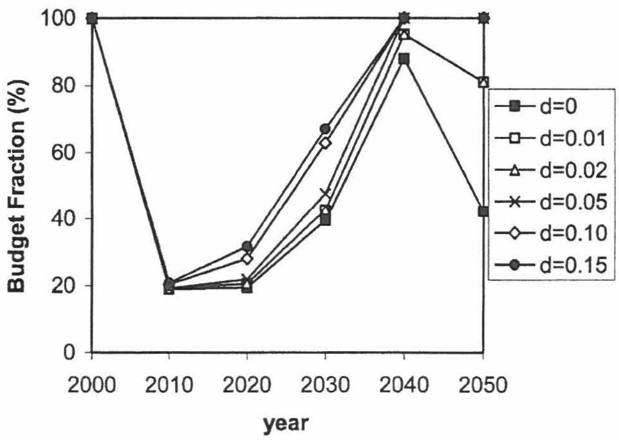

Fig. 4. Expended fraction of the total R&D budget. Different depreciation rates.

conditions. For a given technology, both learning channels (i.e., accumulation of capacity and of knowledge stock) tend to act simultaneously in the model. Without forcing the model to fully allocate the R&D budget, it finds it effective to spend in R&D only once sizeable spending in cumulating capacity takes place. Thus, with this model response, a situation where only one of the mechanisms acts is not observed. Either both of them act "hand-in-hand" or none of them is set in motion.

This behavior of the model must be taken carefully. In reality, R&D expenditures are in many cases a precursor of the accumulation of experience through capacity deployment. Specifically, they can be essential in the first stages of development of the technology, before it goes to the marketplace. This points out that, although the specification of the 2FLC applied here constitutes an important first step in incorporating R&D into the model, the model causality still has to be improved in order to adequately represent the R&D mechanism. Also, this drives to the more general question of the role of both learning channels in different stages of the life cycle of a given technology.

Solar photovoltaic, the technology with the highest LDR and one of the highest LSR, dominates the allocation of R&D resources.[5] The gas fuel cell and the wind turbine also receive significant fractions of the R&D funds. R&D investments in the gas combined cycle turbine, that received the highest amount of resources in the first period, decline and disappear. The same happens to the clean coal technology, having a very low LSR but a relatively attractive LDR, and the new nuclear power plant, with the lowest LDR and LSR. The results are unattractive and R&D investments on them decay along the minimum growth constraint and disappear.

As expected, the technologies with the highest LSR appear to be more attractive for expending R&D resources. However, other factors such as the LDR, the maximum growth rates allowed and the presence or absence of a constraint on emissions, which may force low-carbon technologies into the solution, play also an important role.

The allocation of R&D resources occurs endogenously, guided by the two-factor learning curve and being influenced by the specific set-up of the model and the particular developments in a given scenario. The coupling of the R&D expenditures both with the learning-by-doing mechanism and the other variables in the model, made possible here by its specification as an endogenous contributing factor to the cost reduction, is important because it helps to reflect in the model the fact that market investments and expectations play an important role in whether or not R&D money would be expended on a given technology.

7. Sensitivity to the depreciation rate

The introduction of depreciation of the knowledge stock reduces the effectiveness of R&D as a cost reduction factor as compared to the case where R&D expenditures are simply accumulated. Consequently, it alters the dynamics of allocation of R&D funds in the model. The specific costs of the different learning technologies can be affected by the "forgetting" mechanism. When depreciation is possible the specific costs can increase if not enough R&D is spent in a technology as to keep the knowledge stock at least at previously reached levels. In contrast, cumulative R&D expenditures are a non-decreasing variable and, in such a case, specific costs will only remain at the same level or decline.

The degree to which the cost trends of a given technology are affected by a higher depreciation rate depends on how strong the R&D factor contributes to its cost reduction[6], how attractive are its LDR and LSR as compared to other technologies — which is the size of the R&D budget —, and how cost-competitive is the technology already.

In this section, we examine the effects of different values of the rate of depreciation of the knowledge stock (from 0 to 15% per annum) in the allocation of R&D funds for the test case presented above. As mentioned before, as a simplification the depreciation rate is considered equal for all the learning technologies. Also, it is assumed that the LDR and LSR remain the same as those applied above. In addition, the effects of R&D lags are ignored.

Fig. 4 presents the total amount of R&D expenditures, expressed as a fraction of the budget available in each period, for different values of the depreciation rate. Although the budget is still not fully allocated, with an increasing depreciation rate there is a tendency to augment the fraction of the R&D budget that is spent. At a higher depreciation rate, more funds are necessary to produce the same results in terms of cost reductions and the model decides to invest more in order to counteract the "forgetting-by-not-doing" effect introduced by the depreciation in competitive technologies.

This is an interesting behavior because, in principle, a higher depreciation rate would reduce the attractiveness of investing in R&D. For high depreciation rates, the model could consider it more beneficial either to

[5] This could be regarded as an example of the possibility of having a sort of "lock-in" of the R&D spending in the model. The model may try to continue to assign R&D money to a technology because it makes its cost cheaper and cheaper.

[6] This depends on the relative weight of the learning-by-searching elasticity with respect to the learning-by-doing one, but also on other factors such as the size of the R&D budget and the maximum growth rates of both capacity and R&D expenditures.

invest more in capacity, given that such factor does not suffer depreciation, or simply not to invest in R&D. However, an additional counterbalancing factor intervenes here. No R&D investments would mean "forgetting" and this would translate into increasing investment costs for the different technologies. Thus, there is an incentive to invest in R&D to counteract the "forgetting" effect. Although a definite interpretation of this fact is not possible here, one could probably expect the increasing tendency on the expenditures to last only as long as the model considers the technology attractive enough. These interactions, however, deserve further investigation.

Fig. 5 presents the changes of the share of each technology as the depreciation rate is modified. Solar PV continues to be the most attractive technology across the range of depreciation rates evaluated. However, its share of the R&D budget decreases as the depreciation rate is increased. Investments on the gas fuel cell and the wind turbine also decrease. On the other hand, R&D investments in the gas combined-cycle experience a much slower decline. The new nuclear and advanced coal power plants results are still unattractive, but the amount of R&D expenditures tends to increase.

In the particular case illustrated here, as the depreciation rate was increased, the model shifted towards investing more R&D money to counteract the effect of higher depreciation in the investment cost of the gas combined-cycle, already a very competitive technology that holds the highest share of the generation mix (see Fig. 6). Gas combined-cycle has a very attractive LDR and R&D investments are allocated to it despite the fact that its LSR is very low.

In consequence, given that a limited R&D budget is available, the support to more expensive but promising technologies such as solar PV or the gas fuel cell is diminished, despite the fact that they posses a more attractive LSR. This is an interesting insight of how the model may respond in the presence of a forgetting factor. Still, a more profound examination of the implications of this formulation is necessary.

Finally, Fig. 6 presents the electricity generation mix in the year 2050 under the different depreciation rates. In this CO_2-constrained scenario and taking into account

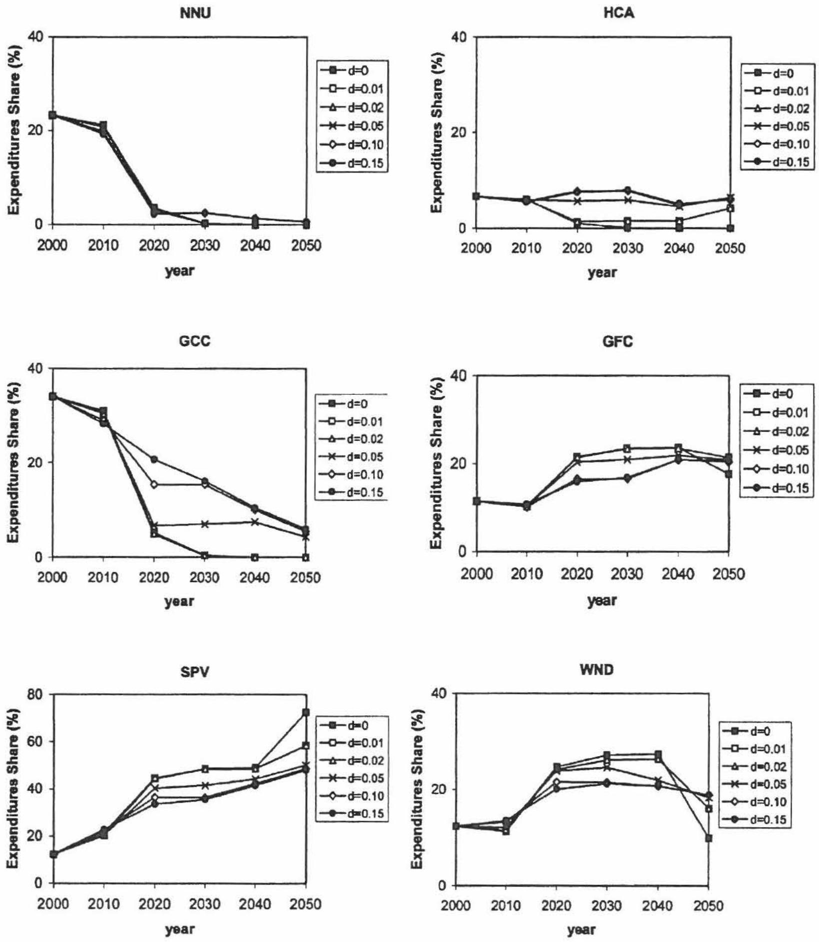

Fig. 5. Share of total R&D expenditures per learning technology. Different depreciation rates.

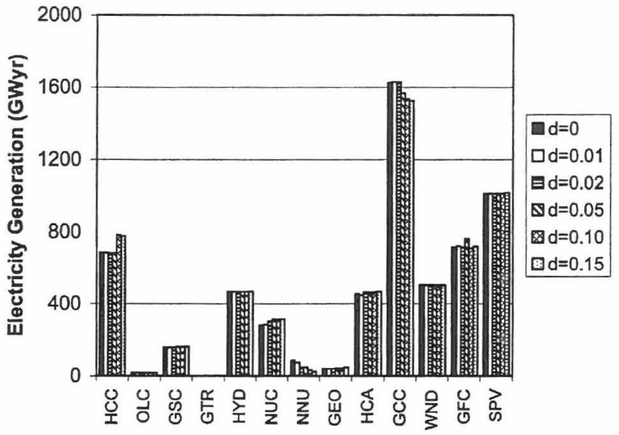

Fig. 6. Electricity generation mix in 2050. Different knowledge stock depreciation rates.

that the cumulative capacity mechanism plays the predominant role in the learning of the technologies considered here, the variations in the generation mix when the knowledge depreciation rate is modified are not large. Still, some technologies alter their outputs. In particular, the gas combined-cycle (GCC) diminishes its electricity generation as the depreciation rate is increased. Despite the injection of R&D funds, the depreciation makes it slightly less competitive. The increasing depreciation rate also affects the new nuclear power plant (NNU), whose output declines substantially. Correspondingly, other technologies are able to increment their share of the market. In particular, the advanced (HCA) and conventional coal plants (HCC) and the conventional nuclear plant (NUC) increase their output.

As mentioned before, in order to develop the exercises presented here, we have made a number of assumptions concerning the knowledge stock, LDR and LSR of the different technologies. However, we do not want to give the reader the impression that those assumptions do not affect the results and we are aware that a number of open issues remain. One particular point that may affect the conclusions derived here is our consideration that LDR and LSR do not change when the depreciation rate is changed. Actually, choosing a different depreciation rate implies that a new statistical estimation of LDR and LSR must be carried out. In that sense, those parameters are not independent from each other. Thus, in order to be meaningful, sensitivity analyses with ERIS must be linked to an assessment of the learning parameters for the technologies involved.

8. Concluding observations and further work

A modified two-factor learning curve formulation is implemented in the energy-systems optimization ERIS model and some illustrative modeling results are presented. The formulation allows for considering the effects of R&D together with those of market experience in the learning process of energy technologies.

The model finds the optimal allocation of a given R&D budget across a set of competing learning technologies using the two-factor learning curve as the guiding allocation rule. The endogenous specification of R&D expenditures makes the allocation of R&D resources dependent on other parameters and variables of the model, such as carbon constraints, specified market penetration constraints, demand growth, etc.

The explicit incorporation of R&D in energy-systems models is important for providing a more comprehensive picture of the technological learning process. Clearly, empirical evidence shows that Research, Development, Demonstration and Deployment (RD3) activities are all important in the energy innovation process and in the successful diffusion of emerging energy technologies. Thus, a more adequate representation of the energy innovation process in the modeling frameworks can be useful, among others, to conduct a more complete examination of energy technology policies. Model analyses may produce insights into how to invest scarce R&D resources more effectively and, thus, they could contribute to more systematic efforts in conforming robust and flexible portfolios of promising new energy supply and demand technologies whose development should be supported.

The knowledge accumulated through R&D efforts is represented here by a knowledge stock function. Such function allows for considering retards between R&D spending and productivity gains (in this case cost reductions) and the fact that past R&D investments depreciate and become obsolete. Through the depreciation rate, a "forgetting-by-not-doing" feature is introduced in the R&D component of the learning process. Leaving aside the effects of accumulating capacity, "forgetting-by-not-doing" implies that if no efforts on R&D are made on a given technology its investment costs may increase. In our particular framework, assumptions concerning the rate at which knowledge depreciates alter significantly the dynamics of allocation of R&D funds. Specifically, faster knowledge depreciation may favor allocating more funds to currently competitive technologies in order to avoid or mitigate their "forgetting" process, rather than allocating them to currently expensive technologies that are promising only in the long run. The possibility of introducing such "forgetting-by-not-doing" characteristic also in the cumulative capacity component of the learning process should be examined carefully.

The approach depends critically on obtaining a statistically meaningful estimation of separate learning-by-doing and learning-by-searching indexes. Problems regarding the quality of the underlying data and the estimation itself remain to be solved. For instance, multicolinearity — that is, high correlation between the two explicative variables (i.e., cumulative capacity and cumulative R&D expenditures or knowledge stock) — arises. One of the reasons for such high multicolinearity can be the fact that each of those variables may respond to changes in the other. Increases in the sales volume, for example, may trigger a higher R&D spending by producing firms, so as to ensure the technology remains competitive in the marketplace. On the other hand, R&D breakthroughs may increase the acceptability of the technology in the market or enable the introduction of new products or services. Methodologies to deal with the estimation problems should be developed. Some promising results appear to have been obtained applying panel data analysis for a set of different countries (Klaassen et al., 2002).

Possible drawbacks of the 2FLC implementation presented here should be analyzed more carefully and alternative approaches should be explored. In connection with this issue, some authors (Watanabe et al., 2002) have pointed out the possibility that the current formulation of the 2FLC implies "duplication" of the factors. The rationale behind such argument is that the cumulative capacity factor already accounts for some product-embodied knowledge stock. Therefore, considering a separate knowledge stock would drive to some double counting of its effects. In this line of arguments, the cumulative capacity factor should be "corrected" to discount the effects of the product-embodied knowledge stock. This proposition deserves further scrutiny.

Alternative approaches have been suggested. Kram (2001) proposes a linear relationship between the learning rate of a single-factor learning curve and a measure of the R&D intensity, which basically assumes that increasing R&D intensity will increase the learning rate of the technology. This relationship has been applied in an exogenous way in the MARKAL model (Fishbone and Abilock, 1981) to assess the impact of additional R&D on the penetration of a given technology. As discussed above, although the use of knowledge stock provides a more complete and sophisticated treatment, its data requirements can be more intensive. If this is so, approaches based on R&D intensity could be favored. However, additional work is required to examine this approach more carefully. On the one hand, the empirical evidence should be analyzed. In particular, it is important to examine whether microstructure changes in the slope of the learning curve (i.e., changes in the learning rate) can be associated with changes in the level of R&D intensity or R&D expenditures. On the other hand, the effects of an endogenous representation of this type of relationship in the models should be examined.

Still, with the limitations and unsolved issues, the introduction of this second factor into the learning curve enables an improved and more comprehensive (though, of course, not complete or definitive) treatment of the factors involved in the cost reduction and allows the modeler to take into account the effects of R&D in energy technology policy in a more direct way. In such sense, this work constitutes a first step towards the incorporation of mechanisms that capture the effects of R&D efforts in the technological progress of energy technologies in the ERIS model.

Traditionally, such effects have been either ignored or modeled in an exogenous way. For instance, awareness of actual, or consideration of future plans for an increased R&D spending could drive to more optimistic considerations regarding future cost and efficiency trends for a particular technology. Also, when applying the standard single factor learning curve, R&D could be reflected as a factor influencing the starting point of the learning curve or the corresponding learning index (see, e.g., Seebregts et al., 1998). Thus, its explicit incorporation in the learning curve and endogenous formulation in the model provide more "degrees of freedom" as to the way its impact and related policy questions may be addressed.

But, increased "degrees of freedom" will very likely imply increased data requirements and, in the absence of reliable data, they will drive to a mounting number of assumptions. Although this certainly will pose difficulties, it should not be a discouraging point. The concept of two-factor learning curves and the work around it have pointed out the need for evaluating the effects of energy R&D investments within the context of technological learning. Moreover, it highlights the need to collect the relevant data, conduct the case studies necessary to evaluate the missing variables and advance in the specification of sound theoretical models.

Among other issues, further work should be devoted to a more elaborated representation of the process of allocation of R&D resources. If possible, the contributions of public and private actors should be differentiated. Also, the possibility of introducing stylized considerations concerning the influence of the technology's life cycle in the relative contributions of market deployment and R&D efforts should be explored. For instance, although in the examples described here both mechanisms act simultaneously for all the learning technologies, one could also consider situations where knowledge can be accumulated on a given technology through R&D before capacity deployment takes place. In addition, although the formulation applied here treats both contributing factors as substitutes, some degree of complementarity between them very likely exists. The examination of their substitutability and/or complementarity characteristics and how they can alter the basic formulation given here is an aspect that deserves a more profound analysis.

In addition, the approach followed here is deterministic. However, long-term future technological developments are highly uncertain and the outcome of technological change processes — in particular the emergence of radical innovations and the "winners", i.e., the technologies that will actually make it to the market — are difficult to predict. Therefore, efforts must be devoted to incorporate uncertainty in the learning characteristics of the different technologies and in other variables in the modeling framework (Grübler and Gritsevskyi, 1997).

Another important issue concerns technological learning spillovers across different regions. That is, the fact that a different world region may benefit from the learning efforts of another region on a given technology. The increasing flows of knowledge and technology across world regions and the rising role of transnational energy technology manufacturers and multi-purpose and highly integrated international energy services companies tend to favor the presence of spillovers at the international level. R&D spillovers play an important role (Papaconstantinou et al., 1998) and should be considered and examined carefully.

In this area there seems to be a number of important topics to be addressed. Studies at the firm level (Cohen and Levinthal, 1989) have shown that firms perform R&D both to keep their own innovative capacity and to be able to assimilate R&D results from other firms, i.e., to profit from learning spillovers. This argument could be extended to the interactions between different world regions. The effects of international spillovers of energy-related R&D will most likely depend on the assimilative capacity of the different regions (e.g., according to the strength of their own science and technology systems). Attempts should be made to capture this interaction, even if only in a stylized way, in energy-systems models.

Other approaches for the incorporation of both learning mechanisms should also be explored. One alternative is the combination of "top-down" and "bottom-up" approaches. As mentioned above, some analyses with "top-down" models (e.g. Buonanno et al., 2000 and Buchner et al., 2002), endogenize technical change in the form of a general R&D knowledge stock that acts as one of the production factors in the economic production function. The R&D knowledge stock enhances the rate of economic productivity and reduces the level of emissions. Technical change can be induced through R&D spillovers across regions. Although this approach provides a way to capture the generic effects of R&D, it does not consider the effects of "learning-by-doing" in specific technologies. The feasibility of combining this type of "top-down" representation of the R&D process with a "bottom-up" model that endogenizes the "learning-by-doing" effect through standard learning curves is worth exploring.

It is still early to establish whether the two-factor learning curve will prove a convenient and sound aggregate model adequately supported by the empirical evidence or sound theory. But, even so, it must be understood as a helpful step towards the development of a more consistent representation of the technological learning process, where both market deployment and R&D efforts contribute to the progress of technologies and interact with each other and other model parameters and variables in a common framework. In addition, this work has made more tangible a number of issues that should be tackled by future research efforts. Clearly, there is still a long way to go in disentangling the role of R&D in the energy innovation system. Substantial efforts should be devoted to address the multiple aspects of this problem.

Acknowledgements

The authors are thankful to Dr. Leo Schrattenholzer, leader of the Environmentally Compatible Energy Strategies (ECS) project at IIASA, for suggesting the incorporation of two-factor learning curves in ERIS and valuable discussions.

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