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Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results

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Abstract

This paper presents the results of using a stylized optimization model of the global electricity supply system to analyze the optimal research and development (R&D) support for an energy technology. The model takes into account the dynamics of technological progress as described by a so-called two-factor learning curve (2FLC). The two factors are cumulative experience ("learning by doing") and accumulated knowledge ("learning by searching"); the formulation is a straightforward expansion of conventional one-factor learning curves, in which only cumulative experience is included as a factor, which aggregates the effects of accumulated knowledge and cumulative experience, among others. The responsiveness of technological progress to the two factors is quantified using learning parameters, which are estimated using empirical data. Sensitivities of the model results to the parameters are also tested. The model results also address the effect of competition between technologies and of CO_2 constraints. The results are mainly methodological; one of the most interesting is that, at least up to a point, competition between technologies—in terms of both market share and R&D support—need not lead to "lock-in" or "crowding-out".

Keywords: Induced technological change; Technological learning

1. Introduction

The effectiveness of research and development (R&D) has been studied at various levels (e.g., Griliches, 1975, 1998; Nordhaus, 1999; Watanabe, 2000; Zhu, 2000), with the clear-cut conclusion that R&D expenditures generally do pay off. Given these general results on the profitability of R&D, questions arise as to how much to spend on R&D and on which technologies. It appears that in the real world, these questions are decided mainly by heuristic rules (Nelson and Winter, 1982). The main reasons for the absence of more quantitative methods include the lack of appropriate tools and the presence of constraints on R&D budgets, which leave little room for optimization. Of course, another reason is the uncertainty concerning the impact of R&D expenditures.

In this paper, we present the results of a methodological experiment using an energy supply optimization model in which we assume cost reductions of electricity supply technologies resulting from the accumulation of capacity and R&D. Cost reduction effects are specified as a three-parameter functional form, which by design permits the determination of optimized levels of R&D support for a given technology.

The functional form of R&D impacts chosen for the experiment here is the so-called two-factor learning curve (2FLC). The 2FLC is an extension of the familiar one-factor learning curve, which stipulates that the costs of producing a manufactured item decrease regularly as a function of cumulative production of that item. The regularity of this decrease is expressed by a power function, which implies that a doubling of cumulative production leads to a decrease in costs by a given fraction, the learning rate. This concept was introduced more than 60 years ago (Wright, 1936), and many learning rates have been estimated for all kinds of manufactured goods. Dutton and Thomas (1984) published a classic survey of learning rates listing more than 100 learning rates in manufacturing. IIASA's Environmentally Compatible Energy Strategies (ECS) Project, among others, has applied this general concept

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specifically to energy technologies (McDonald and Schrattenholzer, 2001).

From a methodological point of view, expressing the cost development of a technology using a simple function of one independent variable, such as cumulative production, is practical and yet still allows for some quite detailed analysis. At the same time, however, this simplicity is also an obvious shortcoming. In particular, looking at such methodology from the point of view of policy-making, the notion that technological progress is dependent on nothing but cumulative production—renders procurement the main policy instrument for accelerating technological progress. Therefore, policy makers—and not just researchers and developers—would wish to see R&D efforts play a role in the explanation of technological progress.

The 2FLC proposed by Kouvaritakis et al. (2000) is formulated using "cumulative production" and "cumulative R&D expenditures" as the two factors. A modified version of this 2FLC is a major feature of ERIS (Energy Research and Investment Strategies, Barreto and Kypreos, 2003), a compact optimization model of the global electricity supply system. In the ERIS model, R&D expenditures and cumulative capacity contribute to technology cost reductions via a 2FLC. We used the ERIS model to analyze the optimal R&D support for an energy supply technology. A brief description of ERIS is given in Section 3.

We consider the analysis presented here to be a first step toward a comprehensive understanding of the dynamics induced by 2FLCs in a compact, stylized model. We started our analysis by calculating optimized R&D support for two technologies, one at a time, using empirically estimated learning parameters (Section 4.1). We used wind and solar photovoltaic electricity generation to represent a situation in which one technology (solar PV) has a long way to go before it reaches competitiveness but has a high potential for technological progress, and the other (wind) is closer to being competitive, but "learns" at a slower pace. The next step was to test the sensitivity of the results with respect to the learning parameters, which were varied around reference values (Section 4.2). Bearing in mind solar and wind energy's obvious attractiveness from the point of view of carbon emission stabilization (Section 4.3), we also introduced carbon emission constraints into ERIS to see how they would affect optimized R&D expenditures.

We then assessed the model with 2FLCs applied to both technologies at the same time. We did this to study how the optimized R&D support of one technology is influenced by the presence of a competitor (Section 5). The analysis thus depicts the situation where two learning technologies compete for R&D support. We had initially used unrealistically low initial specific investment cost assumptions to test the model with input parameters that generated the largest variety of results (Sections 5.1 and 5.2). This meant we were unable to formulate detailed quantitative recommendations at that stage. More realistic (i.e., higher) technology costs assumptions might keep these technologies from entering the energy supply market if cost minimization is the only goal. We therefore concluded by examining a case with carbon dioxide (CO_2) constraints and more realistic investment cost assumptions (Section 5.3). In formulating that case, we intended to reflect the insights gained through the analysis while moving in the direction of policy relevance.

2. The two-factor learning curve

Thirteen energy supply technologies are included in the ERIS model. In this paper, we selected two technologies as learning technologies, and specific costs for eleven other (non-learning) technologies are kept constant (at values given in Table 4). For learning technologies, the unit cost of investment is assumed to decrease as a result of two types of learning, dubbed "learning by doing" and "learning by searching". Accordingly, the learning process is modeled as the 2FLC specified below.

2.1. The 2FLC as used by IIASA-ECS

The concept of learning by doing is well established in the technological-change literature.[1] There is also an extensive literature on the effect of R&D on technological change (see, e.g., the survey by Nelson, 1981). In an attempt to synthesize the two, Kouvaritakis et al. (2000) specified a learning curve with two factors (the 2FLC) describing learning-by-doing and learning-by-searching effects. The 2FLC is a Cobb–Douglas-type function. In the version used here,[2] one factor is cumulative capacity and the other is knowledge stock (cumulative R&D minus depreciation). The choice of a Cobb–Douglas function implies that the relation between knowledge stock and cost reduction is of the same type as the relation between cumulative capacity and cost reduction in the conventional learning-curve representation. Although the empirical evidence for this is rather limited to be convincing, we took this as a first plausible hypothesis.

More specifically, the 2FLC specifies the specific investment cost for each technology te at time t as

$$\mathrm{SC}_{\mathrm{te},t}(\mathrm{CC},\ \mathrm{KS}) = a\,\mathrm{CC}_{\mathrm{te},t}^{-b}\,\mathrm{KS}_{te,t}^{-c}, \tag{1}$$

[1] For a recent survey of leaning-by-doing rates for energy technologies, see, for example, McDonald and Schrattenholzer (2001).

[2] We modified the original formulation of a 2FLC as proposed by Kouvaritakis et al. (2000) by replacing cumulative R&D with the notion of knowledge stock.

where SC is the specific investment cost, in US$('90)/kilowatt (kW); CC the cumulative capacity, in gigawatts (GW); KS the knowledge stock, $-b$ the learning-by-doing index, $-c$ the learning-by-searching index; and a the specific cost at unit cumulative capacity and unit knowledge stock.

For an interpretation of the 2FLC in terms of economic theory of cost and production, see the appendix to this article.

From this definition, we derive two rates—the learning-by-doing rate (LDR) and the learning-by-searching rate (LSR)—in the following way:

$$\mathrm{LDR} = 1 - 2^{-b}, \tag{2}$$

$$\mathrm{LSR} = 1 - 2^{-c}. \tag{3}$$

The interpretations of the LDR and LSR are analogous to that of the learning rate in one-factor learning curves. In other words, assuming no increase of knowledge, specific technology cost decreases at the LDR for each doubling of cumulative capacity; assuming no additions to cumulative capacity, specific technology cost decreases at the LSR for each doubling of knowledge. Although the nomenclature is somewhat arbitrary, it is important to distinguish the learning rate in one-factor learning curves from the LDR in 2FLCs: the latter is designed to explain only part of the phenomenon explained by conventional learning rates in one-factor learning curves.

Knowledge stock is defined as a function of past R&D expenditures that takes into account depreciation and time lags. Following Barreto and Kypreos (2003), we specified the knowledge stock as

$$\mathrm{KS}_{\mathrm{te},t} = \mathrm{KS}_{\mathrm{te},t-1}\,(1-\rho) + \mathrm{ARD}_{\mathrm{te},t-i}, \tag{4}$$

where KS is the knowledge stock, ρ the annual knowledge stock depreciation rate, ARD the annual R&D expenditure, and i the time lag between R&D expenditure and its effect.

Readers may wonder why we included depreciation and time lag for one variable but not for the other. The reason is that we used existing formulations proposed by other authors, and consistency with their work was more important to us than a symmetric treatment of the two factors.

2.2. Numerical values

We chose wind and solar photovoltaic (PV) electricity generation for our analysis of the model dynamics introduced by 2FLC. In addition, the ERIS model also includes eleven technologies for which we assumed constant specific costs over time. We did this to restrict the degrees of model freedom to a manageable number so as to illustrate working of the "learning" mechanism in an isolated way.

Despite the considerable empirical evidence of the importance of R&D in promoting technological progress, attempts to quantify R&D's effect on it have been limited. Some authors have reported finding econometric support for the role of R&D in the context of the learning model (Lieberman, 1984; Goulder and Mathai, 2000). The results of an econometric analysis of R&D effectiveness based on the 2FLC specification have been reported by IIASA-ECS and our collaborators in the EC-sponsored TEEM project (Kouvaritakis et al., 2000; Criqui et al., 2000; Klaassen et al., 2002).

The learning parameters for the two technologies selected for this analysis were estimated using global time series data between 1971 and 1997 which were collected and estimated by Criqui (2000) as a contribution to the same TEEM project (EC-TEEM, 2000). Original cumulative-capacity data are primarily from UN-ENERDATA, and were modified by Criqui. R&D expenditures here include both private and business R&D. Data on public R&D is from IEA's government energy R&D statistics, and business R&D is estimated from 44 key companies collocated at IEPE.

As an example of investment cost information, Fig. 1 shows the specific investment cost, expressed in US$('90) per kilowatt of installed capacity, for wind and solar PV between 1971 and 1996. Solar PV exhibits a steep cost reduction, whereas wind shows a more modest one. At the same time, the cumulative installed capacity up to 1997 for wind (7.63 GW) is larger than that for solar PV (0.40 GW), although both are insignificant in terms of electricity market shares. This choice of technologies therefore allows us to compare a technology that still has a long way to go to reach competitiveness but that has a high potential for technological progress (solar PV) with another technology that is closer to competitiveness but that "learns" at a slower pace (wind).

We estimated the learning parameters using ordinary least squares. In doing so, we experienced instability in the form of low correlation coefficients and low significance of the estimated parameters, most likely

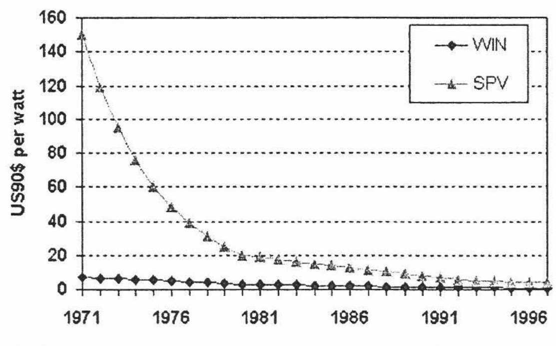

Fig. 1. Development of specific investment cost of wind electricity and solar PV. Data: Criqui (2000).

Table 1
Results of learning parameter estimations for solar PV and wind power

	Solar PV	Wind
Learning-by-doing rate (LDR), % (estimated)	17.46	9.73
t-statistics	−18.20	−7.93
Learning-by-searching rate (LSR), % (fixed)	10	10
R^2	0.94	0.80

Table 2
Numerical values used in the analysis

	Solar PV	Wind
Initial knowledge stock, billion US$(98)	14.9	5.2
Annual knowledge depreciation, % per year	3.0	3.0
Time lag for knowledge effectiveness, years	2	2
Learning-by-doing rate (LDR), %	17.5	10
Learning-by-searching rate (LSR), %	10	10

due to multi-collinearity,[3] as was also reported in Kouvaritakis et al. (2000). We adopted the solution used by Kouvaritakis et al. (2000); that is, we fixed the elasticity with respect to the knowledge stock at different levels while estimating the learning-by-doing elasticity econometrically. The numerical results with some test statistics are presented in Table 1.[4] These estimates were then used as reference values and as a basis for sensitivity analysis with ERIS. The parameters defining the knowledge stock from R&D expenditures are summarized in Table 2. Initial knowledge stock has been calculated based on Formula (4), using the public R&D data from the dataset of Criqui (2000). The annual knowledge depreciation rate has been taken from Criqui, and the value of the time lag for knowledge effectiveness has been taken from Watanabe (2000). Other input parameters, such as electricity demand development and maximum annual production limits, were taken from the B2 scenario which was contributed to the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emission Scenarios (SRES, Nakićenović et al., 2000). The discount rate was 5%.

3. The ERIS model

ERIS was built by Barreto and Kypreos (2003). Optimizing the modified ERIS model includes determining the optimal levels of R&D expenditures, in particular the interplay between the benefits of the two factors, learning by doing and learning by searching.

3.1. The objective function in ERIS

ERIS minimizes the sum of all discounted direct energy costs (investment, operating and maintenance, and fuel costs) plus R&D costs (expenditures). R&D is thus determined endogenously.

The objective function of the ERIS model therefore is as follows:

$$\text{Total Cost} = \sum_{t=1}^{T}[(\text{TEC}_t + \text{ARD}_t)(1+d)^{-t}], \tag{5}$$

where TEC is the direct energy cost (annual), ARD the annual R&D expenditure, d the discount rate, and T the end year.

The annual total energy cost is calculated by summing the energy costs for each technology. Total energy costs consist of the investment, operation and maintenance, and fuel costs:

$$\text{TEC}_t = \sum_{\text{te}}(\text{ICOST}_{\text{te},t} + \text{OMC}_{\text{te},t} + \text{FC}_{\text{te},t}), \tag{6}$$

where TEC is the direct energy costs (annual), ICOST the investment costs, OMC the operation and maintenance costs, and FC the fuel costs.

Capacity expansions for different technologies are also the result of the cost minimization, but they are subject to market penetration constraints, which limit the speed of buildup of a technology. In practice, these constraints turn out to be binding, at least for the early periods of the diffusion of a new technology.[5]

3.2. Methodological remarks

The cost-reducing effect of increasing the cumulative installation of a technology is referred to as "increasing returns to scale." This, in general, leads to the existence of more than one local optimum (points of locally minimum costs) of the objective function.[6] Moreover, the local minimum points are not necessarily of equal size and, more important, they are not necessarily close to one another in the feasible regions defined by the model constraints. We illustrate such a situation in Fig. 2.

Fig. 2 illustrates a complex example of a non-convex objective function of two variables. In a much simpler

[3] In this case, multi-collinearity means that the two explanatory factors depend on each other. If this is so, the effects of the two factors cannot be reliably separated.

[4] We also estimated the equations with fixed elasticity for learning-by-searching but the statistical fit was in general poor compared with the cases of fixed elasticity for learning-by-doing.

[5] Market penetration constraints limit the (relative) growth of new technologies. For energy systems, many pieces of empirical evidence (see, e.g., Marchetti and Nakićenović, 1979) gave rise to incorporating this kind of constraint into ERIS—as well as into many other energy supply models.

[6] Most commercial software generates just one local optimum. The user has at times difficult task of deciding whether the optimal point identified by the software is a global or just a local optimum.

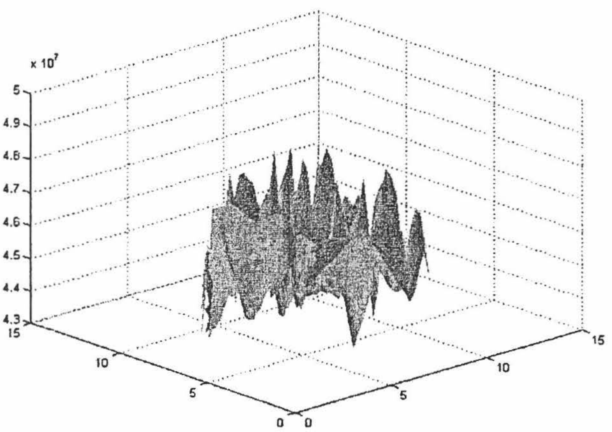

Fig. 2. Illustration of a non-convex objective function of two variables. Source: Gritsevskyi and Ermoliev (1999).

ERIS case, for example, these different points could represent the costs of two systems of electricity generation, one with full utilization of a new learning technology and the other without any significant contribution from it. There would be no local optimum between these two, because if a learning technology is competitive at one point in time it becomes even more competitive with each installation of a new plant. This phenomenon is often termed "path dependency" (Arthur, 1990). In Fig. 2, this can be visualized by imagining that once a system moves towards the direction of local minimum, it is optimal to remain there. The historical path thus determines to which of the many local minima, depicted in the figure, the system moves to.

For solving ERIS, we used a solver with Non-linear Programming (NLP) capabilities. With this solver, the main task in finding the *global* optimum is to find a starting point for the NLP that leads to it. In the comparatively simple cases reported here, this did not present a problem because we never included more than two learning technologies in any model run. However, with an increasing number of technologies, this could become quite a difficult task, because two local minimum points can be expected per learning technology (one with and one without that technology). Ten technologies would then have 1024 (2^{10}) local minimum points.[7]

4. Results for single learning technologies

In this section, the results of the ERIS model are presented for a situation where only one technology is learning. We begin by presenting the "reference case," where learning parameters are set to the values estimated at the beginning of the study. The majority of the sensitivity analysis concerns the effect of changes in the two learning parameters on optimized R&D expenditure. However, we also analyze the influence of a CO_2 constraint.

[7] Meanwhile, solvers are being developed, that can identify and find global minima (Sahinidis, 2000).

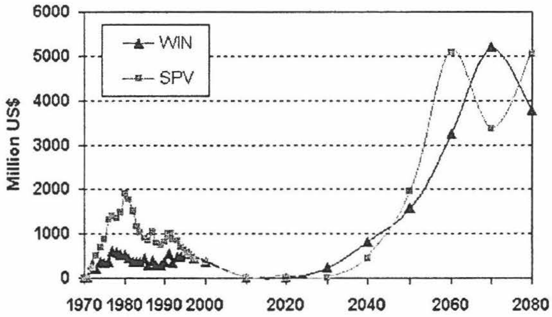

Fig. 3. R&D expenditures for wind and solar PV power generation after 1990 (reference case), optimized separately by ERIS, and actual R&D expenditures before 1990.

4.1. Reference cases

Our first set of experiments with the ERIS model concerned the levels of optimized R&D expenditures in the hypothetical situation of an unlimited R&D budget.

Fig. 3 shows the optimized levels of the R&D expenditures calculated separately for wind and solar PV up to 2080, together with their actual development between 1971 and 1997.[8] An analysis of the trajectories of R&D support and installed capacity shows that higher capacities go along with higher R&D expenditures. This means that in the world of the ERIS model, R&D is most effective, when its diffusion takes off.[9]

The figure also shows that ERIS finds optimized levels of R&D support that begin to exceed today's levels after the year 2040. For both technologies considered here, there is a "hole" of optimized R&D support in the near future. This means that, under reference conditions, the model tells us that the time for intensive R&D support is still to come for wind and solar PV, that is, in the model world it is optimal to intensively spend R&D support later, at a time closer to the competitiveness of the two technologies.

[8] The model time horizon actually extended to the year 2100, but boundary effects lead to unrealistic results for the last two decades of this period. The reason is that the benefits of reduced technology costs extend beyond the model's time horizon. Thus the benefits of R&D spent late in the time horizon are not considered—or are only partially considered—during the optimization.

[9] This, however assumes that a technology has reached a state of maturity as described by our initial conditions and does not say anything about the very early stages of invention and prototype development of a technology.

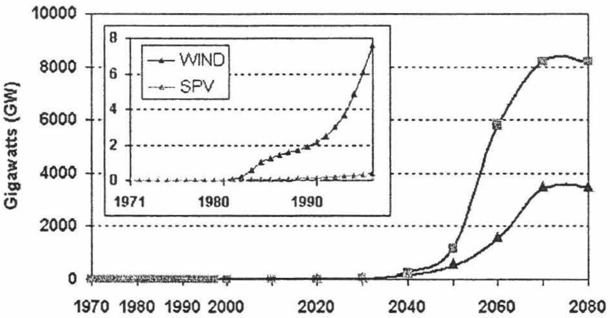

Fig. 4. Installed capacities for wind and solar PV power generation after 1990, optimized by ERIS, and actual cumulative capacities before 1990. The trajectories prior to 1995 are enlarged in the insert for better readability.

In ERIS, new installations include replacements of capacity that goes out of service. New installations are therefore equal to the difference between installed capacities *plus* replacements. This—and the constraints on total installed capacity—leads to a (somewhat artificial) wave-like evolvement of capacity additions over time, and the same pattern is reflected in optimized R&D support.

Fig. 4 shows actual past and optimized future installed capacities. Installed capacities for both technologies remain at an insignificant level until 2030. However, after 2040 the technologies are installed rapidly, and in 2070 the share of installed capacity for wind reaches nearly 20% and that for solar PV reaches 35% of the total electricity generating capacity. These shares may appear unrealistically high, but generous upper limits were chosen so that the model dynamics could be studied more readily.

The model results concerning the buildup of wind and solar PV are mostly the outcome of ERIS' market penetration constraints. Their interplay with the 2FLC will become apparent during the sensitivity analysis described in Section 4.2.

4.2. *Sensitivity analysis*

Analyzing the sensitivity of non-linear models is extremely important, even more so than for linear models. We concentrated on testing the sensitivity of the model results concerning optimized R&D expenditures with respect to the two learning indices of the 2FLCs.[10] The mid-point for the ranges within which we vary the learning coefficients are those reported in Section 2.2. The model results we analyze concern optimized R&D levels for the learning technology as a function of the two learning parameters.

4.2.1. *Varying only the learning-by-searching rate*

First, we looked at the optimized levels of R&D keeping the LDR fixed at our reference value and varying the LSR from 1% to 30%. The development of the optimized R&D support between 2000 and 2080 is presented in Fig. 5 for wind power generation. The figure shows that as a general rule, higher LSRs correspond to higher levels of R&D support, indicating that if a technology is more "responsive" to R&D (expressed by higher LSRs), then more R&D support is found to be optimal. This effect saturates, however, and for LSRs at the high end of the spectrum, we find a optimized R&D expenditures that are lower than for lower LSRs. The reason for this outcome can be found in the market penetration constraints included in ERIS. These constraints prevent the model from reaping higher benefits from a higher responsiveness of a technology to R&D expenditures as soon as the LSR passes a threshold.

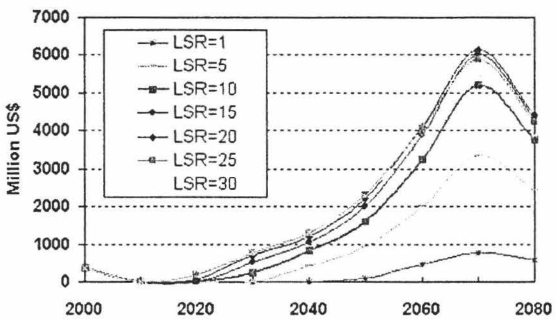

Fig. 5. Development of optimized R&D expenditures for wind power generation, LDR fixed at 10%. The reference case (LDR = 10 and LSR = 10) is represented by a bold line.

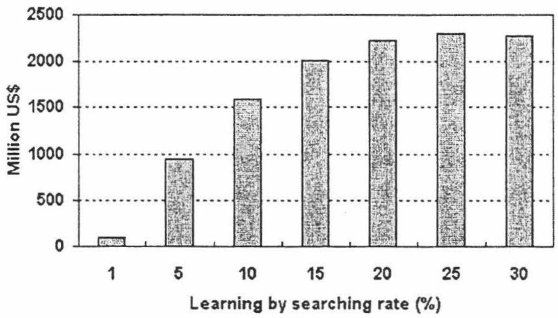

Fig. 6. Optimized R&D expenditures for wind power generation in 2050, LDR fixed at 10%.

[10] In addition to the learning-by-searching index, the effect of the knowledge factor on cost reduction is sensitive to the parameters of the formula that defines knowledge as a function of R&D expenditures. Varying these parameters would therefore also vary the responsiveness of a technology to R&D expenditures. This variation is not exactly the same as the one introduced by the learning-by-searching index, but we think that varying the latter is sufficiently representative of varying all these parameter together.

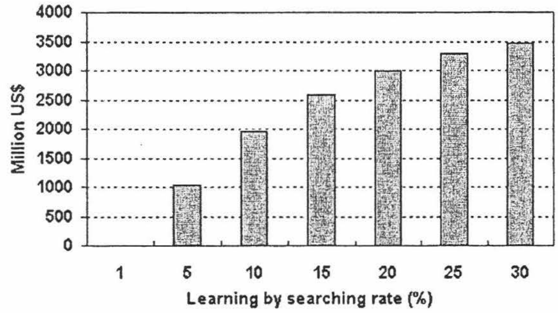

Fig. 7. Optimized R&D expenditures for solar PV power generation in 2050, LDR fixed at 17.5%.

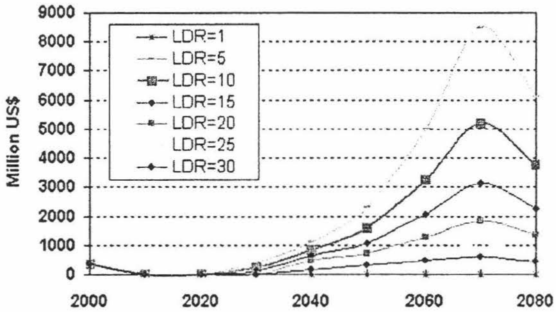

Fig. 8. Development of optimized R&D expenditures for wind power, LSR fixed at 10%. The reference case (LDR = 10 and LSR = 10) is represented by a bold line.

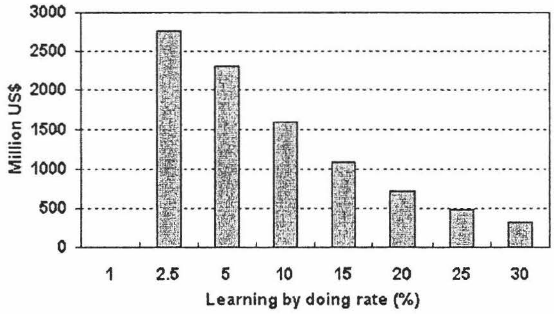

Fig. 9. Optimized R&D expenditures for wind power in 2050, LSR fixed at 10%.

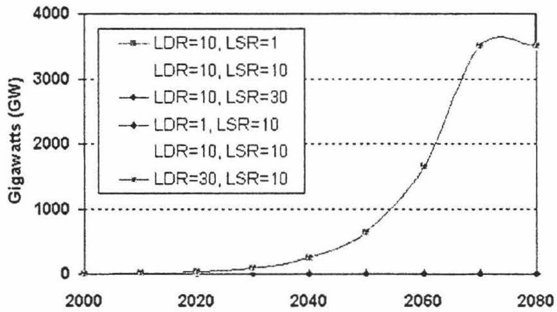

Fig. 10. Installed capacity of wind power for different pairs of parameters for the 2FLC (the zero-capacity case corresponds to LDR = 1, LSR = 10).

This pattern is further illustrated in Fig. 6, which shows this dependence for the year 2050 only. Here we can see that there seems to be an upper limit to this effect. If the LSR is higher than a certain value, in this case 25%, this effect disappears.

The same kind of analysis (constant LDR, varying LSR) was done for solar PV power generation (Fig. 7). The general picture is the same as for wind, with one exception at the low end of the LSR (LSR = 1%). As we shall see later (Fig. 10), this case corresponds to zero installed capacity, which means that solar PV does not enter the market for such a low LSR. Optimized R&D expenditures again appear to reach an upper limit, but only at an LSR higher than those depicted in Fig. 7.

4.2.2. Varying only the leaning-by-doing rate

We also calculated the optimized R&D support with a fixed LSR but varying LDRs. The results of these calculations for wind power are presented in Figs. 8 and 9, which show the development of the optimized R&D expenditure over time and in 2050, respectively.

Fig. 8 demonstrates that, in general, higher LDRs correspond to lower levels of R&D support, indicating that if a technology is more likely to progress as a result of learning by doing, then less R&D support is needed to reach its optimized cost reductions. By the same token, smaller LDRs suggest that additional R&D expenditures can compensate for a technology's lack of responsiveness to experience (cumulative capacity).

Fig. 9 again shows lower optimized levels of R&D support at higher LDRs, with one exception on the low end of the LDR spectrum considered here. When the LDR is equal to only 1%, wind technology does not enter the market, and an LSR of 10% (the reference value) is not high enough to alter this result.

In the next step, we studied the interplay between installed capacity and different values for the two learning rates. Fig. 10 shows that there are only two distinct trajectories of wind capacity in all cases, one at zero installation and the other at the reference case. The fact that the two cases of non-zero installations are identical reflects the market penetration constraints, which limit the speed at which wind technology is introduced. Once the model finds that it is worthwhile to introduce this technology—characterized by given learning parameters—it introduces the technology to the limit specified elsewhere in the model. If the model does not find it worthwhile to introduce the technology, no investment takes place, leading to no new installations of this technology.

Optimized R&D expenditures for solar PV in the year 2050 (Fig. 11) show a pattern similar to that obtained for wind power. As the investment costs of solar PV are higher than those for wind power, it takes a higher

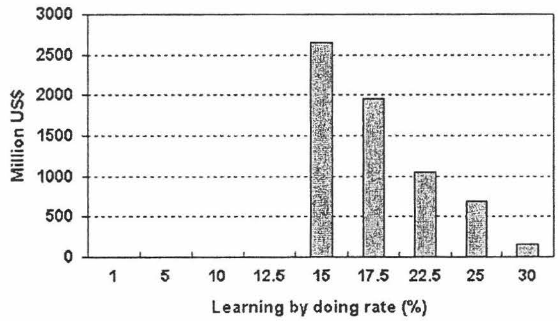

Fig. 11. Optimized R&D expenditures for solar PV power in 2050, LSR fixed at 10%.

"threshold" LDR (of 15%) to bring the technology into the market. Likewise, the trajectory of the installed capacity for solar PV shows the same "all-or-nothing" situation (with LDR = 1, LSR = 10 as the zero-capacity case) as seen in the case of wind, and is therefore not presented graphically here. One trajectory reaches maximum electricity production by solar PV in 2070, and the other stays at insignificant levels of installed capacity.

To summarize, the learning rates affect the optimized R&D levels in opposite ways. Higher LSRs result in higher optimized R&D expenditures, implying that more R&D investment pays off. Accordingly, investment cost reductions are steeper when LSRs are high.

In contrast, higher LDRs lead to lower optimized R&D expenditures. This is because when learning by doing is more effective than learning by searching (i.e., there is greater cost reduction from capacity accumulation than from R&D), cost reductions can be achieved more effectively through capacity accumulation and R&D money can be saved instead of being spent to reduce the cost.[11]

4.3. CO_2 constraints

One reason for the popularity of renewable-energy technologies is that they emit less CO_2 than those fueled by fossil energy. We therefore included a CO_2 emission constraint in ERIS to see how it influences the results, primarily those concerning optimized R&D expenditures. Solely for illustrative purposes, we constrained CO_2 emissions from global electricity production to below the 2020 level of the non-constrained case.

Two brief points are worth making concerning the CO_2 emission constraints. First, in principle, the introduction of the constraints does not change the levels of R&D support. Both wind and solar PV power generation continue to receive the same amount of R&D support as without the carbon constraints. This is because the installed capacity path has already followed its maximum path and thus does not change as a result of the introduction of the constraints. However, in the cases with unconstrained CO_2 emissions, this did not hold for selected combinations of learning parameters. This leads us to our second point: in some of the cases where a renewable-energy technology previously did not enter the market because of its less responsive learning properties, the introduction of the constraint changes the situation. The technology now enters the market (with maximum market penetration), and thus the technology, which previously did not receive R&D support, now does. The amount of R&D that technologies receive fits to the picture drawn in the Section 5.2. In other words, the continuous dependence of optimal R&D expenditure for a changing learning parameter remains if we plot optimal R&D expenditure calculated with the CO_2 restriction.

If a technology had already entered the market in the absence of carbon emission limits, optimized R&D remains unchanged. This is again a consequence of the "all-or-nothing" observation mentioned above. Therefore, all that a carbon emission constraint does is to change the optimal capacity from zero to maximum in close cases.

5. Technologies competing for R&D support

So far, we have reported ERIS runs in which only one technology was learning at a time. Our next step was to incorporate both wind and solar PV power generation into ERIS at the same time to determine whether supporting one technology can be so profitable that technology becomes the only one to receive R&D support; that is, it "crowds out" the other technology.

5.1. Reference case

5.1.1. Optimized paths of R&D expenditures and installed capacity

For this phase of the analysis, we used the learning rates summarized in Table 1 for solar PV and wind energy as a reference case and then moved on to a sensitivity analysis with respect to different learning indices. Fig. 12 shows the optimized R&D expenditures calculated by ERIS for the reference case where wind and solar PV learn at the same time.

The figure shows that the optimized R&D expenditures for one technology are independent of the presence of the other technology. The two trajectories are identical to those we found when we let the technologies learn separately. We also made a run with the carbon

[11] This result is in some ways analogous to the concept of *optimal value shares* in Cobb–Douglas functions. There, higher exponents of one production factor lead to higher optimal value shares. Similarly, relatively more effective learning by doing (a higher LDR) leads to a relatively lower "value share" of knowledge, that is, lower R&D expenditures and vice versa.

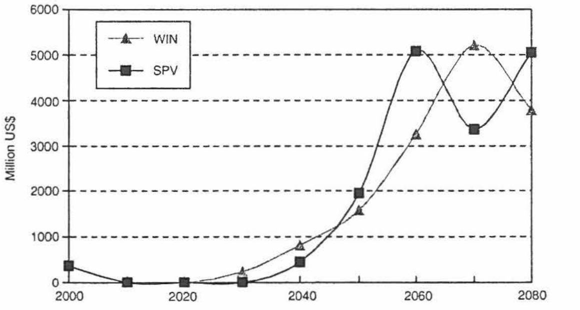

Fig. 12. Time evolution of R&D expenditures for wind (WIN) and solar PV (SPV) energy technology.

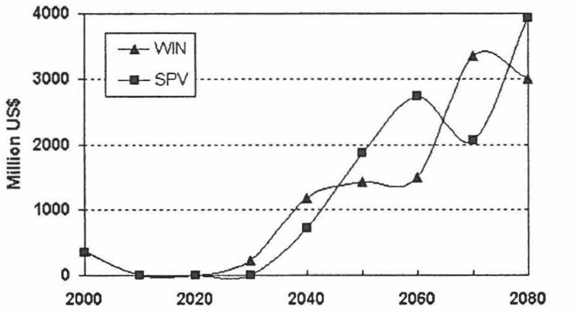

Fig. 13. Time evolution of R&D expenditures for wind (WIN) and solar PV (SPV) energy technology assuming a limit on the R&D budget.

emission constraints as we did in Section 4.3 for single-technology cases and found that they do not change the optimized R&D expenditure for the two technologies compared with the case without the constraints.

Regarding the installed capacities, the optimized cumulative capacity in the case where the two technologies learn together was identical to that in the case with a single learning technology (Fig. 4). In other words, optimized R&D expenditures in our case are a function of the learning characteristics of the two technologies and not the result of competition between them.

As this result was not entirely expected, we repeated the experiment, this time incorporating a budget constraint.[12] Fig. 13 illustrates the optimized R&D expenditures for the two technologies under the assumed R&D budget constraint. A comparison with Fig. 12, where no R&D limit was set, reveals that the evolution over time for the two cases is quite similar, but that the absolute levels are reduced in the case of the budget constraint. It is worth mentioning that even in the presence of the R&D constraint, each technology continues to receive R&D support and stays in the market. A budget constraint in ERIS therefore does not lead to a discontinuation of support of one technology in favor of supporting the other.

This result suggests that, for decisions on optimal R&D support, what is most important is estimating (with the help of 2FLCs, for example) the responsiveness of a technology to R&D. In the single-technology case, where there was no competition, this point was perhaps more obvious, but here the model results show that in the given situation, the importance of competition is only secondary.

5.1.2. Total system costs

Our total system costs consist of investment costs, operation and maintenance costs, fuel costs, and R&D expenditures. Numerical results of system cost items for the reference case are presented in the first column of Table 3. To determine cost savings resulting from R&D spending, we also performed a model run with an R&D budget restriction setting R&D at zero (second column of Table 3). We calculated the difference in the total discount system costs of the zero-R&D run and the reference run as the cost reduction effect due to R&D spending, which came out to be US$54.7 billion. If this value is compared with the R&D expenditures (US$14.9 billion), the benefit of the R&D is 3.7 times the R&D expenditures.

These results should be regarded as mere illustrations of numerical results of a model that includes several simplifying assumptions. They may serve as an indication of the orders of magnitude involved, but there is no realistic way that they can be interpreted as quantitative policy guidance.

Looking at undiscounted costs, we arrive at the values shown in Fig. 14. The figure confirms the generally high profitability of R&D expenditures under the assumptions made in the model.

5.2. Sensitivity analysis

In this section, we present the results of a sensitivity analysis of the two-technology learning case, focusing on the sensitivity of the optimized R&D expenditures for the two technologies with respect to their learning parameters. In our study, we investigated whether optimized R&D support of one technology remains unaffected by the presence of the other technology—even when the learning parameters of the other technology are varied—as was the result in the reference case. Our main finding was that it remained unaffected. In all the cases of two technologies learning together that we looked at, we obtained the same result for optimized R&D and capacity expansion of the learning

[12] The assumed budget constraint limits the available total R&D budget for the two technologies to approximately 15% of the government R&D budget for IEA countries in 1997 (IEA, 2000) but takes into account that the level grows with GDP growth (based on the MESSAGE B2 scenario from Nakićenović et al., 2000). Fifteen percent is an arbitrary number but it is the level that limits the R&D spending to 50% of what has been calculated as the optimal level in the non-limited case for 2060.

Table 3
Comparison of total discounted cost and R&D expenditure

	Reference case	No R&D case	Difference between the two
Total discounted system cost, billion US$(98)	14,318.6	14,373.3	54.7[a]
Total discounted R&D expenditure, billion US$(98)	14.9	—	14.9[b]
Net R&D benefit ([a] – [b])	—	—	39.8

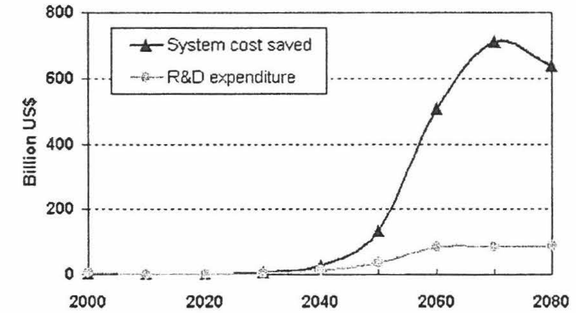

Fig. 14. Development of non-discounted system cost saved due to R&D (gross R&D benefit) and non-discounted R&D expenditure.

technologies as we would have achieved had we simply combined the corresponding cases in which only one technology was learning at a time.

Fig. 15 presents selected graphical results obtained from our sensitivity analysis. The figure illustrates the optimized R&D allocation between the two renewable technologies according to different learning parameters for the wind technology. The learning parameters for solar PV are fixed. The reference case is presented as a bold line. The left-hand side of the figure is the case where the LDR for wind is changed; the right-hand side is the case where the LSR for wind is changed.

5.3. *A more realistic scenario*

Throughout most of our analysis, we emphasized the methodological aspect of running ERIS. Therefore, rather than using the most realistic values we could find, we chose model input parameters that generated particularly dynamic model outputs. Nonetheless, our eventual goal is to use ERIS results to generate policy-relevant insights. Thus, as a first step in that direction, we ran one case with numbers that were more realistic, but still close to those in the other cases reported here to maintain comparability.

For this case, we used one of the runs with a CO_2 emission constraint as a basis. Instead of the unrealistically low cost figures (800 US$/kW for wind and 1800 US$/kW for solar in the year 1990), we used 1035 US$/kW for wind and 5000 US$/kW for solar. The carbon emission constraint was as in Section 4.3.

Fig. 16 illustrates the optimized levels of the R&D expenditures. As a comparison between this figure and Fig. 12 shows, the biggest differences between the two cases are that the more realistic case shows higher levels of optimized R&D (increases of 25% for wind and more than 140% for solar PV) than the less realistic case. Not surprisingly, Fig. 17 shows that the optimized installed capacities for both technologies remain the same compared with the previous runs. As could be expected, the higher the initial specific investment cost, the higher the optimized R&D.

Fig. 18 shows the development of the specific investment costs for wind and solar power generation. The specific investment cost for wind gradually drops to 194 US$/kW; for solar it drops as low as 132 US$kW. This is the combined effect of the two factors, learning by doing (cumulative capacity) and learning by searching (knowledge stock) (Table 4). Figs. 19 and 20 show the percentage change (compared with the previous decade) of the specific investment cost for wind and solar power, respectively, decomposed into the effect of learning by doing and the effect of learning by searching. One phenomenon common to both technologies is that during the earlier periods of our time horizon, a decreasing knowledge stock (caused by zero or low R&D expenditures) increases the specific investment cost. In other words, according to ERIS it is optimal to allow the knowledge accumulated in the periods prior to the model's time horizon to depreciate. After 2040 in the case of solar and after 2030 in the case of wind, new capacities of the two technologies are again being built, accompanied by further R&D expenditures.

6. Summary and conclusions

The results of the ERIS model runs presented in this article provide the basis for understanding the model, in particular the optimization behavior that results from the formulation of a 2FLC. In addition to cumulative experience, which is mathematically the sole factor in conventional one-factor learning curves, the 2FLC used in ERIS includes knowledge as a second factor. Knowledge is a function of R&D expenditures, a time lag, and knowledge depreciation.

We obtained several qualitative and quantitative results from our ERIS model runs. As we have stressed, the entire exercise was stylized in the sense that we emphasized model dynamics rather than realistic input

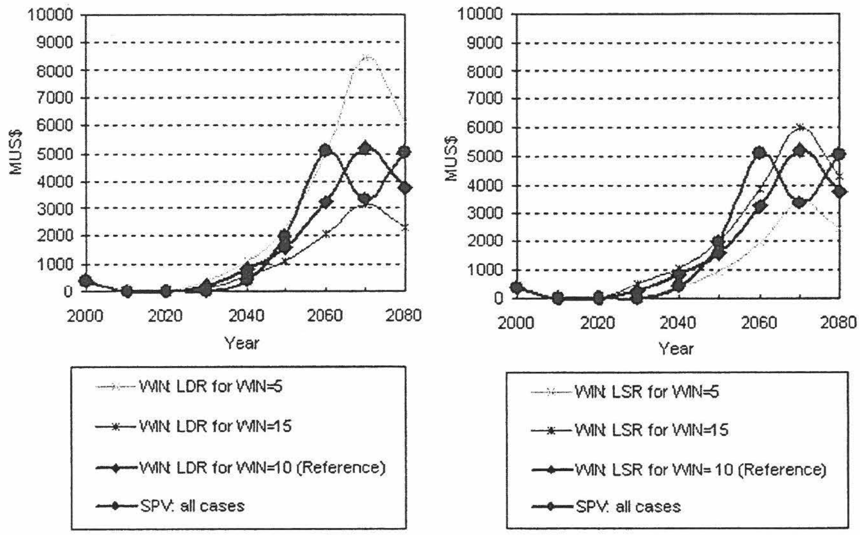

Fig. 15. Time evolution of optimized R&D expenditures for wind (WIN) and solar photovoltaic (SPV) energy technology when the learning parameters for SPV is fixed for all cases. LSR is fixed for WIN at 10% (LDR = 5%, 10% (reference), and 15%, respectively) [left part]; and LDR is fixed for WIN at 10% (LSR = 5%, 10% (reference), and 15%, respectively) [right part].

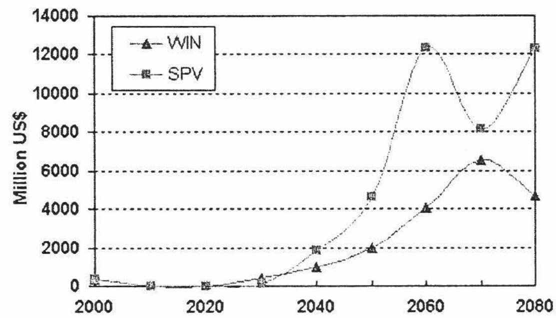

Fig. 16. Optimized R&D expenditures for wind and solar PV power generation, optimized separately by ERIS.

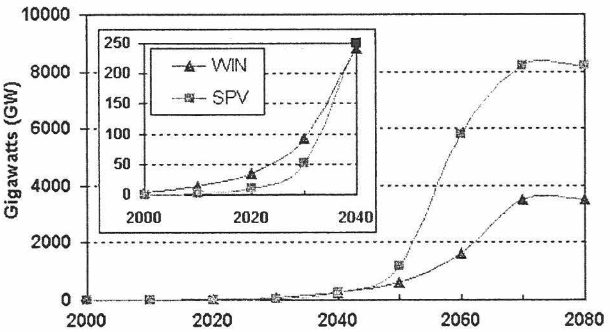

Fig. 17. Installed capacities for wind and solar PV power generation, optimized by ERIS.

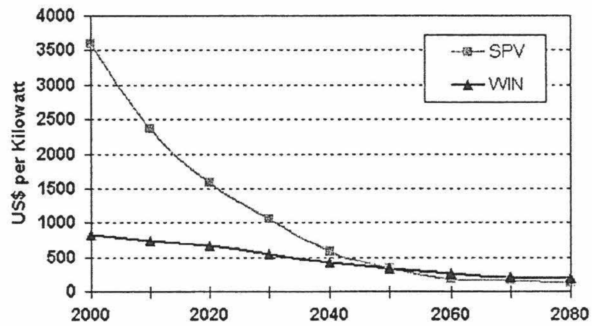

Fig. 18. Specific investment cost development for wind and solar PV power generation.

Table 4
Specific investment cost assumptions for non-learning technologies

Technology name	US$('90) per kW
Conventional coal-fired power plant	1357
Conventional oil-fired power plant	1575
Gas steam cycle power plant	988
Gas turbine	350
Hydroelectric power plant	3562
Geothermal power plant	3075
New nuclear power plant	3400
Conventional nuclear power plant	3075
Advanced coal power plant	1584
Gas combined-cycle power plant	600

data. This was done because we think that understanding the model results as they change in response to changing 2FLC parameters is a necessary point of departure from which policy implications could be derived only during further work.

To study the interplay between technologies described by 2FLCs, we included two such technologies—wind and solar photovoltaic power generation—in our analysis. Our first area of interest was the question of whether the optimal R&D support of a learning

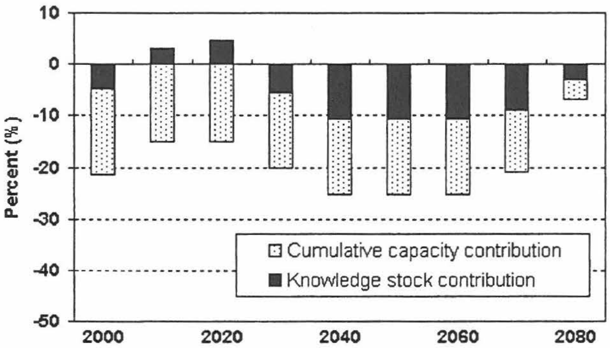

Fig. 19. Decomposition of the cost-reduction factors for wind.

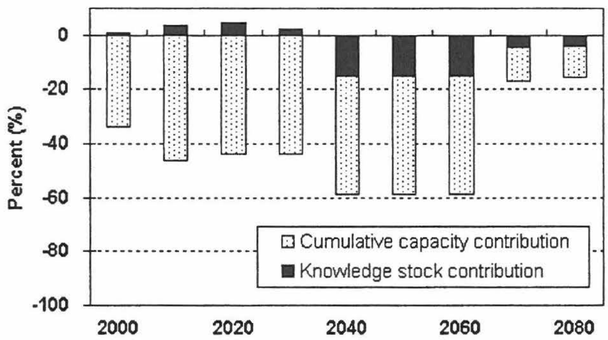

Fig. 20. Decomposition of the cost reduction factors for solar PV.

technology would be unrealistically high if a budget constraint were not included. In other words, we wanted to know whether the budget constraints that prevail in the real world would be required to prevent ERIS from generating optimization results suggesting R&D support levels beyond any realistic R&D budget.

To answer this question, we first analyzed the optimized R&D levels for the reference case for each technology separately. Although the orders of magnitude of actual past R&D support and optimized R&D expenditures calculated by ESRI for the future are the same, we observed a break in the trend. After a decline during the initial periods, current levels of R&D spending are reached again only in 2040. This is because the R&D support for solar PV and wind power is effectively used only when there is a bigger market. This model result does not say anything about the early stages of technological research, because the initial condition of ERIS's 2FLCs assume that a technology concept has already passed the threshold of technical feasibility.

From the sensitivity analysis of the 2FLC parameters we can identify some of the robust results concerning optimal R&D allocation. One robust result is that if only one technology is found to respond profitably to R&D support, the optimized levels of R&D move continuously—that is, without jumping—as a consequence of small changes in one of the learning rates. In general, the optimized levels of R&D are sensitive to both learning parameters, but in different directions. Higher LDRs correspond to lower levels of optimized R&D support, whereas higher LSRs correspond to higher levels of optimized R&D spending.

The transition from high to zero R&D support is the only major jump (discontinuity) we observed. The expression "bang-bang" (or "all-or-nothing"), often used to characterize the solution behavior of Linear Programming models, applies here in the sense that a technology either never enters the electricity market or quickly enters it to the limits defined elsewhere in the ERIS model, most notably the market penetration constraints. This phenomenon also explains why there is not much to analyze in terms of a possible tradeoff between spending money on procurement (capacity expansion) versus on R&D support.

As a next step, we analyzed cases where two technologies learn at the same time. We found that optimized R&D allocation for one technology is independent of the presence of the other technology. The competition between the technologies, both in terms of R&D support and market shares, turns out to be of secondary importance. What matters for both is whether the combination of the technology's own learning parameters warrants its profitable deployment—just as in the case of only one learning technology. The allocation of R&D support to one of the two technologies is also independent of the learning parameters of the other technology. We therefore identified a situation in which the often-cited phenomena of "lock-in" (the dominance of one learning technology at the expense of the other as a consequence of increasing returns to scale) and "crowding-out" (a limited R&D budget that leaves room for supporting only one technology) were not observed. This does not mean that we question the results of other authors (for example, Arthur, 1990; de Feber et al., 2002), but it means that in a case in which they are used as arguments for or against particular R&D investments, care should be taken to ascertain that a situation as described here could be excluded.

Of course, our observations on the competition between the two technologies are also a consequence of the limited availability of the two technologies, both of which have to rely on the intermittent nature of their primary-energy source. First priority for our future work is the formulation of cases in which many, or less constrained, technologies learning as described by 2FLCs are included. This will allow us to analyze the interaction of technologies, in particular between established and new technologies. When the results of such cases are analyzed, the conclusions presented here will have to be revisited.

Other future work will also include refining 2FLCs parameter estimates and searching for more appropriate functions describing the responsiveness of technologies to R&D activities. Even if such functions are found, we believe that any quantitative impact of R&D on technological progress will continue to be surrounded by uncertainty. For this reason, our future methodological work will include stochastic modeling in which R&D effectiveness will be described by a random variable.

Whatever the results of our future work, we expect that the solution dynamics of a stylized model as presented here will prove useful for understanding the results of more sophisticated methods in the future.

Acknowledgements

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Appendix A. Underlying economic theory of cost and production for the learning-curve model

The following description is based on Berndt (1996):

We define the production function for the energy capital producer with using a Cobb–Douglas-type specification:

$$y = A\, l^{\alpha}\, k^{\beta}, \tag{A.1}$$

where y is the output in constant prices, l the labor input in constant prices, k the capital input in constant prices, and A the technological change.

The cost function dual to the production function (A.1) is calculated as[13]

$$\ln C = \ln a + \frac{1}{\gamma}\ln y + \frac{\alpha}{\gamma}\ln p_l + \frac{\beta}{\gamma}\ln p_k - \frac{1}{\gamma}\ln A, \tag{A.2}$$

with

$$a = \gamma(\alpha^{\alpha}\,\beta^{\beta})^{-1/\gamma},$$

where C is the cost at current prices, p_l the labor price (deflator), p_k the capital price (deflator), and γ the scale effect (defined as $\gamma = \alpha + \beta$) (if $\gamma = 1$, constant return to scale, $\gamma > 1$, increasing return to scale, $\gamma < 1$, decreasing return to scale).

Taking the learning concept from the 2FLC, we define A as

$$A := \mathrm{CC}^{-d}\mathrm{KS}^{-s}, \tag{A.3}$$

where CC is the cumulative capacity and KS the knowledge stock.

Substitution of Eq. (A.3) into the cost function (A.2) gives

$$\ln C = \ln a + \frac{1}{\gamma}\ln y + \frac{\alpha}{\gamma}\ln p_l + \frac{\beta}{\gamma}\ln p_k + \frac{d}{\gamma}\ln \mathrm{CC} + \frac{s}{\gamma}\ln \mathrm{KS}.$$

The unit cost is expressed as

$$\ln\frac{C}{y} = \ln a + \frac{1-\gamma}{\gamma}\ln y + \frac{\alpha}{\gamma}\ln p_l + \frac{\beta}{\gamma}\ln p_k + \frac{d}{\gamma}\ln \mathrm{CC} + \frac{s}{\gamma}\ln \mathrm{KS}. \tag{A.4}$$

We now compare the unit cost function (A.4) and the 2FLC. We define the 2FLC as

$$\mathrm{SC} \equiv \frac{c}{y} = B\,\mathrm{CC}^{-d}\,\mathrm{KS}^{-s}, \tag{A.5}$$

where c is the cost in real prices

The 2FLC (A.5) follows from the unit cost function (A.4) if we make two assumptions. The first assumption is that the combined price index of labor and capital can be approximated by a GDP deflator as follows:

$$\ln p_{\mathrm{GDP}} = \frac{\alpha}{\gamma}\ln p_l + \frac{\beta}{\gamma}\ln p_k. \tag{A.6}$$

The second assumption is constant returns to scale, which is

$$\gamma = 1. \tag{A.7}$$

Putting Eq. (A.6) and (A.7) into the unit cost function (A.4) yields the 2FLC (A.5)

$$\ln\frac{C}{y} - \ln p_{\mathrm{GDP}} = \ln a + \frac{1-\gamma}{\gamma}\ln y + \frac{d}{\gamma}\ln \mathrm{CC} + \frac{s}{\gamma}\ln \mathrm{KS},$$

$$\ln\frac{c}{y} = \ln a + d\ln \mathrm{CC} + s\ln K.$$

[13] Eq. (2) is a result of the cost minimization problem

$\min C = p_l\, l + p_k\, k$

subject to

$y = A l^{\alpha} k^{\beta}$

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