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Introducing errors in progress ratios determined from experience curves

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Abstract

Progress ratios (PRs) derived from historical data in experience curves are used for forecasting development of many technologies as a means to model endogenous technical change in for instance climate–economy models. These forecasts are highly sensitive to uncertainties in the progress ratio. As a progress ratio is determined from fitting data, a coefficient of determination R^2 is frequently used to show the quality of the fit and accuracy of PR. Although this is instructive, we recommend using the error σ_{PR} in PR, which can be directly determined from fitting the data. In this paper we illustrate this approach for three renewable energy technologies, i.e., wind energy, bio-ethanol, and photovoltaics.

Keywords: Experience curve; Progress ratio; Error propagation; Wind energy; Bio-ethanol; Photovoltaics

1. Introduction

Experience or learning curves are widely used in policy and scenario studies in many fields [1–7] to account for technology development. These curves illustrate that technical and economic performances of a technology increase substantially as producers and consumers gain experience with this technology. This typically is reflected as a substantial reduction in production costs. This phenomenon was first described by Wright [8], who reported that unit labor costs in airframe manufacturing declined significantly with

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accumulated worker experience: this cost reduction was of a constant percentage with each doubling of cumulative output. Plotted on a log–log scale this empirical relationship is displayed as a straight line, and simple extrapolation allowed for assessment of possible future airplane cost. Wright's discovery nowadays is termed "learning curve", as he only measured the effects of learning-by-doing, i.e., he determined the time required to complete a certain task and used that to determine the reduction in labor. The notion that this learning-induced cost reduction was the product of experience was introduced in the 1960s by Arrow [9]. The Boston Consultancy Group some 10 years later extended the learning curve concept in two ways [1]. First, it was applied to the total cost of a product, thereby including other learning mechanisms such as research, development and demonstration (RD&D) and economies of scale, and other cost factors (e.g., cost of capital, marketing, overhead). In order to distinguish them from simple learning curves they were labeled "experience curves". In addition, the concept was applied not only within a single company, but also to entire industries.

Different approaches have been developed to further conceptualize knowledge and learning [2,10–19]. Among these approaches are, listed in order of increased market penetration of a technology: learning-by-searching, learning-by-doing, learning-by-using, learning-by-interacting, upsizing, and economies of scale. Learning-by-searching is the most dominant mechanism in the early phase of technology development, but often may play an important role at later stages as well. Niche-market development follows learning-by-doing and is important in learning-by-using. Increased diffusion of the technology leads to learning-by-interacting. Upsizing, such as in upscaling gas turbines, may lead to reduced unit cost and, finally, mass production occurs in the last stage. Combinations of these approaches may occur in each stage of technology development and may also be time-dependent. Effects of learning and scale effects are often differentiated in order to simplify the experience concept, however, even then, overlap is present, which complicates analysis of technology development [20]. The learning approaches described above are used to explain the mechanisms behind cost development; an experience curve is a means to quantify this in an aggregated way. Also, understanding technology development is attempted by disaggregating experience curves, by performing a bottom–up analysis of cost development of important components of that technology, see, e.g., [19,21].

Forecasting technology development is based on extrapolating a historical trend to the future, thereby assuming sustained trends [22], as was first done by Wright [8]. Long-range forecasts are used in planning possible future solutions to socio-economic problems of which the climate problem is the most pressing [7,15,23,24]. In developing scenarios that assist in describing the solutions to various problems, endogenous technical change is now featured in most leading climate–economy models, as recently reviewed by Köhler et al. [24]. In their review with extensive references they compare existing models and also describe the main limitations: "the lack of uncertainty analysis; the limited diffusion of technology; and the homogeneous nature of agents in the models including the lack of representation of institutional structures in the innovation process" [24]. A point of critique Köhler et al. raise is that only limited sensitivity analyses are applied in comparison to the vast parameter space possible. A wide range of future images is possible as a result of the large amount of variables in these models; nevertheless multiple scenario analyses are limited. They further conclude, among others, that "incorporating uncertainty will be a major challenge for the current generation of climate–economy models" [24].

In many studies experience curves have been constructed on the basis of historical data that span several decades [25,26]. From these curves a "progress ratio" PR is determined, which is the relative amount of cost reduction per doubling of cumulative output. The "learning rate" is then defined as one minus PR. Progress ratios have been found to vary between 0.5 and 1.0 for the semiconductor industry [22], manufacturing firms [25], and energy technologies [26].

Given the empirical nature of the experience curve data and related inherent uncertainties, the PR is likely to vary to some extent [25], when key parameters are changed such as the assumptions about initial capacity installed, the associated start-off costs, the method of aggregating annual data, correcting for inflation and varying exchange rates, and changing the learning system boundaries [27]. Already small changes in PR can lead to strongly deviating results for (long-term) scenarios and energy models using experience curves to model endogenous learning [28–30]. For example, a variation of the progress ratio for photovoltaics (PV) technology has an enormous influence on the cost of reaching break-even, which is defined as the cumulative production at which PV is competitive with conventional electricity generating power plants [31]. Van der Zwaan and Rabl estimate the break-even unit cost to be $1/Wp, which coresponds to bulk electricity prices of about US$0.04/kWh [31]. For a progress ratio of 0.80 they calculated that the break-even cumulative production would be 148 GWp, which is reduced to one-third for a progress ratio of 0.75, but increased more than six-fold for a progress ratio of 0.85. Note that the present (2005) cumulative production is about 6 GWp [32]. The cost of reaching break-even can be calculated by integrating the experience curve, which results in 211, 74, and US$1240 billion for a progress ratio of 0.80, 0.75, and 0.85, respectively [31]. This example clearly illustrates the importance of using "correct" values of the progress ratio. Of course, it is unclear what the "correct" value is. To date, most studies rather present ranges in between which PR may vary, and recommend using these ranges in scenario analyses in climate–energy models [21,27,33,34]. In order to better justify such ranges we propose to use the error in PR, e.g., 0.80 ± 0.05. In this paper, we will show how this error can be determined from fitting experience curve data. Although the margins of error in the PR value were first discussed by Alchian in airframe manufacturing on the basis of declassified World War II data [35], it is still not a common practice to specify this error in the PR value.

The determination of PR involves fitting historical data that span one or more decades, and resulting values for PR are given in two or three digits following the decimal point. Usually, but not always, the coefficient of determination R^2 associated with reported values for PR is given, which indicates certain accuracy in these values. In a study on the influence of varying R^2 on PR error we have found that progress ratios with associated $R^2 \sim 0.9$ have errors of about 0.01 [36]. Progress ratios with associated $R^2 < 0.8$ have appreciable errors of > 0.02, therefore, specification of PR values in three digits is not always correct.

We have discussed above that a small variation of PR can have a large effect on outcomes of scenario analyses. In order to justify a specific variation of PR the error in PR should be used. This error can be determined from fitting experience curve data, and it will serve as a justification of the range of PR in sensitivity studies that scenario developers perform. Therefore, the objective of this paper is to present a simple method to accurately determine the error in the value of PR. We show that one can easily deduce this error from the definition of PR: it depends on the error in the slope of the double-log plot. The slope and its error result from chi-square minimization fitting. To illustrate the usefulness of this method, we will determine the error in PR for three renewable energy technologies, i.e, wind farms, bio-ethanol, and photovoltaics. With these examples, we provide the range of PR values that scenario makers should use to parameterize endogenous technical change in their climate–economy models.

2. Theoretical considerations

In this section the methodology being used in determining the error in PR, denoted as σ_{PR}, is presented. It will be shown that fitting parameters and associated errors are needed to calculate σ_{PR}. Therefore, the basics of chi-square minimization fitting are presented. As values for PR are reported usually in conjunction with the coefficient of determination R^2 of the fitted data, its definition is also given.

2.1. Experience curve

The empirically found relation between the cost and the cumulative production in a wide range of products has also been analyzed theoretically [1–4,6,16,22,25,26]. A power function well describes this relation, although other functions have been proposed as well [2]. Usually, double logarithmic graphs clearly demonstrate a linear relationship, where the slope is a measure of learning or experience; hence the term learning or experience curves. Such a curve can be described as:

$$c_x = ax^m \quad \text{or in logarithmic form} \qquad \log c_x = \log a + m \log x \tag{1}$$

in which c_x is the costs required to produce the xth unit of production, x the cumulative production up to and including the xth unit of production, a the costs required to produce the first unit, and m the measure of the rate of costs reduction as cumulative production increases. The constant parameter m also is denoted learning or experience parameter, and is used to calculate the progress ratio PR for cumulative doubling of production:

$$\mathrm{PR} = \frac{c_{x_2}}{c_{x_1}} = \frac{ax_2^m}{ax_1^m} = 2^m \quad (\text{for} \quad x_2 = 2x_1). \tag{2}$$

The learning rate LR is then defined as:

$$\mathrm{LR} = 1 - \mathrm{PR}. \tag{3}$$

Both progress ratio and learning rate are expressed in ratios or percentages. Values for progress ratios typically range from 1.0 (100%) to 0.5 (50%), with a mean around 0.8 (80%), Possibly, the value of PR may be dependent on technology [22,25,26]. Note that in practice cost data are not readily available, and price is used as a proxy for cost.

The error σ_{PR} in the progress ratio can be calculated from error propagation theory as given by Bevington [37]:

$$\sigma_{\mathrm{PR}} = \left(\frac{d(2^m)}{dm}\right)_m \sigma_m = \ln 2 \cdot 2^m \cdot \sigma_m = \ln 2 \cdot \mathrm{PR} \cdot \sigma_m. \tag{4}$$

in which σ_m is the error in parameter m, resulting from the fitting procedure.

2.2. Fitting

The experience curve as shown in Eq. (1) can be generalized as:

$$y = f(x;a,m) \tag{5}$$

in which y is the dependent variable, x the independent variable, $f()$ the function describing the dependency between y and x, and a and m the parameters used in the function $f()$. Chi-square minimization is widely used as a standard way of defining the best fit: it minimizes the sum of the squares of the vertical differences between the experimental curve and a (non)-linear theoretical curve of choice. The reduced chi-square χ_r^2 is defined as [37]:

$$\chi_r^2(a,m) = \frac{1}{n-p}\sum_i w_i[y_i - f(x_i;a,m)]^2 \tag{6}$$

in which $n-p$ is the degrees of freedom, n is the number of data points (x_i,y_i), p the number of parameters (in this case 2, i.e., a and m), and w_i the weight associated with the ith data point (here taken as $w_i=1$, i.e., unweighted fit). Minimization of χ_r^2 is often done by using the Levenberg–Marquardt method [38,39], which is implemented in many (non)-commercial data analysis software tools, see e.g. Ref. [40]. Standard errors in parameters can be calculated using co-variance matrices [37], in which the goodness of the fit is reflected, i.e., small errors correspond in general to a good fit. The error σ_m of the parameter m is used in determining the error in PR σ_{PR} as defined in Eq. (4).

Another way of determining a best fit involves the use of the coefficient of determination R^2 (also known as goodness-of-fit parameter), which is defined as the ratio of the regression sum of squares to the total sum of squares [37]:

$$R^2 = \frac{\sum_i \left[f(x_i;a,m) - \frac{1}{n}\sum_i y_i\right]^2}{\sum_i \left[y_i - \frac{1}{n}\sum_i y_i\right]^2}. \tag{7}$$

The coefficient of determination R^2 varies between 0 and 1 and denotes the strength of association between y and $f(x;a,m)$. Fitted data with R^2 value larger than 0.8 are considered strongly correlated, whereas fitted data with $R^2<0.25$ are weakly correlated [37]. Fitting strongly correlated data also yields small values for the standard error in σ_m, and consequently small errors in σ_{PR} through Eq. (4).

3. Results and discussion

The methodology described above is used in this section for three renewable energy technology cases, i.e., wind farms, bio-ethanol, and photovoltaic technology, to demonstrate the usefulness of introducing an error in the value of the progress ratio. Published data are fitted to determine PR and its error σ_{PR}.

3.1. Wind farms

Global experience curves for wind energy farms have been constructed only recently [27]. Before that, only regional data or data per manufacturer were analyzed to yield progress ratios varying between 0.68 and 1.17. Junginger et al. review this data and further discuss the effects of system boundaries on experience curve analysis [27]. Fig. 1 shows the global experience curves for wind farms for Spain and the United Kingdom (UK) over the periods 1990–2001 and 1992–2001, respectively. Reported values for PR are PR=0.81 (R^2=0.978) for the UK and PR=0.85 (R^2=0.887) for Spain [27]. In addition, for Spain it was reported that PR=0.82 (R^2=0.875) for the period 1990–1998.

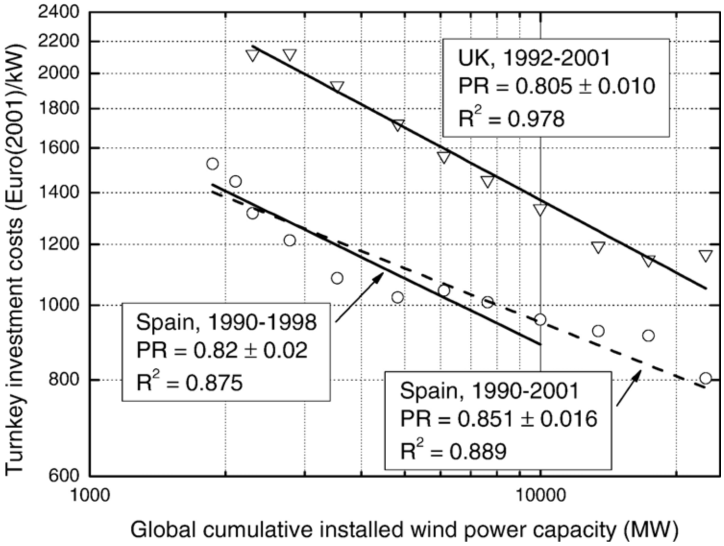

Fig. 1. Wind farm experience curve: turnkey investment costs in Euro (2001) per kW as a function of global cumulative installed wind power capacity in MW for wind farms in Spain (1992–2001) and the United Kingdom (1990–2001). Original data are from Junginger et al. [27].

Our fitting analysis of the wind park experience curve as depicted in Fig. 1 shows that for the UK data PR equals 0.805±0.010 with $R^2=0.978$ for the period 1992–2001. Analysis of the Spanish data shows that PR=0.851±0.016 with $R^2=0.889$ for the period 1990–2001, whilst PR=0.82±0.02 with $R^2=0.875$, or nearly 4% lower for the period 1990–1998. However, the difference is not significant, due to the respective errors of 2 and 3%. The values themselves are in excellent agreement with the PR as determined by Junginger et al. [27]; we have determined an error in these values.

3.2. Bio-ethanol

Recently, Goldemberg et al. [41–43] have presented the Brazilian experience with bio-ethanol from sugarcane as provided by the Brazilian Alcohol Program [44]. The ethanol experience curve apparently shows a discontinuity in the year 1985, as depicted in Fig. 2. Ethanol prices (in US$ of October 2002) decrease in the period 1980–1985 with a progress ratio of 0.93, whilst in the period 1985–2002 the price decrease is very much faster with a progress ratio of 0.71 [42]. Unfortunately, the quality of the fits as expressed by the coefficient of determination R^2 was not reported, whilst data spread is considerable, see Fig. 2.

Our fitting analysis of the bio-ethanol experience curve as depicted in Fig. 2 shows that in the period 1980–1985 PR equals 0.932±0.011 with $R^2=0.887$; in the 1985–2002 period we find PR=0.71±0.02 with $R^2=0.885$. These values are in excellent correspondence to the values of PR as given by Goldemberg et al. [42]; however we have determined an error in these values. The data point of the year 1999 is an outlier in statistical terms and largely influences the fitting result as its value is about half the values of 1998 and 2000. The cause behind this is the deregulation of the market in 1999 in combination with an extremely productive harvest season leading to an overcapacity of cane and sugar [45]. If we exclude this data point from the analysis we find for the period 1985–2002 PR=0.724±0.015 with $R^2=0.938$. Obviously, the value of PR is

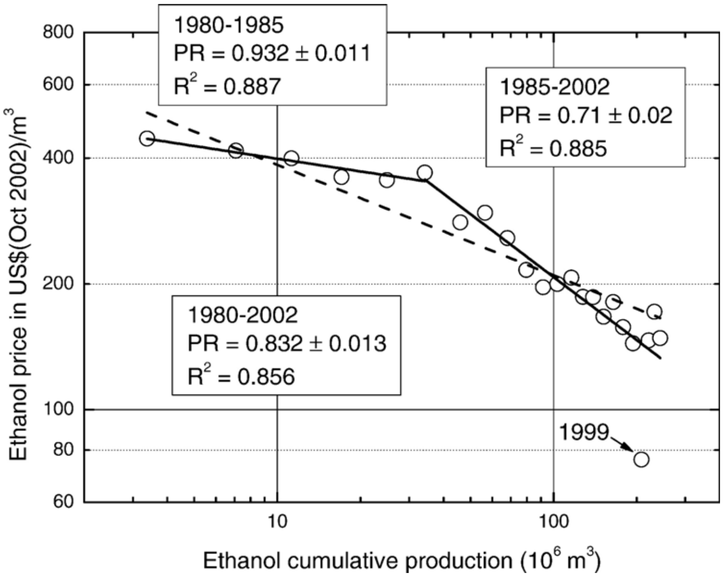

Fig. 2. Ethanol experience curve: ethanol price in US$ (Oct 2002) as a function of cumulative ethanol production in millions of m^3 for Brazil for the period 1980–2002. Original data are from Goldemberg et al. [42].

somewhat larger and has a lower error as R^2 has improved. For comparison, fitting the complete data set (1980–2002) we find PR=0.832±0.013 with R^2=0.856; see the dashed line in Fig. 2.

3.3. Photovoltaic technology

Progress ratios for PV technology have been used to assess the prospects and diffusion of PV [5,31,46–49]. Harmon [50] and Parente et al. [51] recently updated PV experience curves on the basis of price data from Maycock [52]. Harmon reported a PR of 0.798 with R^2=0.9927 [50], whilst Parente showed that a statistically significant break occurs in 1991: in the period 1981–1990 a PR was determined of 0.798 (R^2=0.977), whilst in the period 1991–2000 a 3% lower PR was determined of 0.774 (R^2=0.978) [51]. Fitting the complete curve (period 1981–2000) yielded PR=0.772 with R^2=0.988. A moving average analysis with a time window of 10 years has shown [48] that PR is not constant and may vary between 0.84 and 0.7 for 10-year periods starting from 1976 to 1992, with low PR values in the most recent time-windows. Associated R^2-values are between 0.84 and 0.98.

The global PV experience curve used in the present analysis is depicted in Fig. 3, in which the average selling price of photovoltaic power modules in 2001 US$ as a function of cumulative shipments is shown for the period 1976–2001 [47,53]. Fitting the complete (1976–2001) curve yields PR=0.794±0.004 with (R^2=0.992). Following the analysis by Parente et al., we have also analyzed the data covering the two periods 1981–1990 and 1991–2000, see Fig. 3. We arrive at PR=0.834±0.016 (R^2=0.913) for the period 1981–1990, and PR=0.704±0.015 (R^2=0.975) for 1991–2000, illustrating that PR is not constant.

As Parente et al. reported errors in the fitting parameter m [51], we can use these to determine the error in PR with Eq. (4). We thus arrive at the values shown in Table 1; for comparison also results of our own analysis are shown. Clearly, there are considerable differences between the analysis results. One possible explanation may be the difference in sources of data. We have used data for the period 1976–2001 from

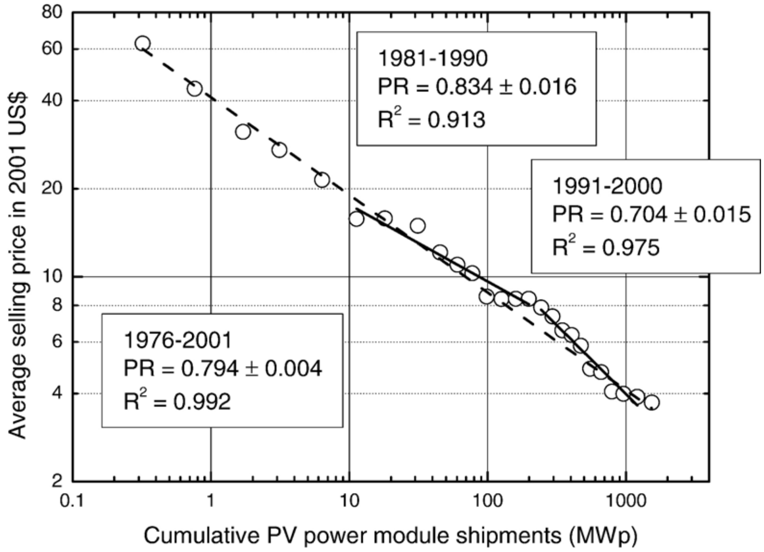

Fig. 3. PV experience curve: average selling price in US$ (2001) as a function of cumulative PV power module shipments in MWp for the period 1976–2001. Original data are from Strategies Unlimited [47,53].

Strategies Unlimited [47,53], whilst Parente et al. have used data from Maycock [52]. Nemet [54] recently also reported on the discrepancy in values for PR as a result of using different data sources: he presented PR = 0.74 and 0.83 resulting from Maycock [52] and Strategies Unlimited data [47,53], respectively. The discrepancy is caused by the fact that the largest differences between these data sources occurs in the years up to 1985, which has a large effect on fitting results [54]. A study further elucidating the origin of the differences in the data clearly is required.

The question remains what the "correct value" of the progress ratio is. The determined error in all PR values is around 0.01, but the difference in all PR values induced from using different data sources is around 0.05. Thus, using the error in PR to justify the range in scenario analyses in climate–energy models in this case would lead to a range that would be too narrow. Nevertheless, in an attempt to arrive at a value of PR we compare the values of PR for the longest periods (1981–2000) in Table 1 with the value for the whole period (1976–2001) as the errors are smallest for fitting long periods. Note, we thus ignore the apparent accelerated cost reduction in the period 1991–2000. The value of PR determined from Strategies Unlimited data for the

Table 1
Comparison of progress ratios determined from fitting various time periods

		1981–1990	1991–2000	1981–2000
Parente et al.	PR	0.798±0.010	0.774±0.011	0.772±0.010
	R^2	0.977	0.978	0.988
Present study	PR	0.834±0.016	0.704±0.015	0.816±0.009
	R^2	0.913	0.975	0.954

The errors in the results from Parente et al. are calculated from their data [51]. The present study uses original data reported by Strategies Unlimited [47,53].

period 1976–2001 is between the values for the 1981–2000 periods and has the lowest error. Averaging these values and errors leads to PR = 0.794 ± 0.014.

4. Conclusion

In this paper we have described a methodology to include an error in the value of the progress ratio. This was motivated by the fact that uncertainty in climate scenarios nowadays is assessed by limited sensitivity studies only. As the consequences of a small variation of the progress ratio can be enormous in forecasting scenarios, the inclusion of an error in the progress ratio provides scenario developers with the smallest necessary range over which sensitivity studies should be done.

We recommend that the determination of progress ratio from experience curves should include determination of the error as well. For the calculation of the error σ_{PR} we have derived a simple equation that can be used in standard spreadsheet software.

To illustrate the method, three technology examples were given. Analysis of wind farm development in the United Kingdom was shown to yield 0.805 ± 0.010 for the period 1992–2001; for Spain we found PR = 0.851 ± 0.016 for the period 1990–2001. Fitting analysis of the bio-ethanol experience curve showed that PR = 0.832± 0.013 for the period 1985–2002. The values of PR determined by our fitting method are in excellent agreement with the reported values for wind farm and bio-ethanol development, and we have added an error to these values. The case of PV technology development yielded PR = 0.794 ± 0.004 for the period 1976–2001, based on a dataset from Strategies Unlimited [47,53]. Comparison with results reported by Parente et al. [51] revealed a clear difference in PR values, which apparently is due to the fact that another dataset, from Maycock [52], was used. The difference in PR values is larger than the error σ_{PR} that we determined. A "correct" value of PR is therefore difficult to specify, and a detailed study on the origins of the difference in datasets is needed.

Scenario developers can directly use the PR values and their errors that are reported here for justification of the range of PR in sensitivity studies. They should be aware that progress ratios may not be constant, although historical data provide evidence that assuming constant progress ratios is a valid approach to include endogenous technological learning in their climate models. Re-evaluating progress ratios when new data become available is therefore always needed and updating experience curves should be part of technology development research.

The presented calculation method may be limited by the use of data sets that consist of one data point per year. These data points are determined by averaging several data points available for a particular year. The resulting data points are taken as being accurate, i.e., as having no error, whilst determination of the standard error of the mean is easy. In fact, using errors in these data points in fitting the curves, will lead to larger errors in the progress ratio. One may even consider weighted fitting. Therefore, the error in PR as presented here for the three technology cases should be regarded as the lowest that one can determine. We therefore recommend that in future studies experience curves should be depicted and fitted using errors also in individual data points. Scenario developers should choose their range in sensitivity studies using the error in PR as the lowest bound of their range.

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References

[1] Boston Consulting Group, Perspectives on Experience, BCG, Boston, 1972.
[2] L.E. Yelle, The learning curve: historical review and comprehensive survey, Decis. Sci. 10 (1979) 302–328.
[3] J.A. Cunningham, Using the learning curve as a management tool, IEEE Spectrum, 1980, pp. 45–48.
[4] M.B. Liebermann, The learning curve and pricing in the chemical processing industries, RAND J. Econ. 15 (1984) 213–228.
[5] L. Neij, Use of experience curves to analyse the prospects for diffusion and adoption of renewable energy technology, Energy Policy 25 (1997) 1099–1107.
[6] C.-O. Wene, Experience Curves for Energy Technology Policy, OECD/IEA, Paris, 2000.
[7] B. Van der Zwaan, R. Gerlagh, Climate sensitivity uncertainty and the necessity to transform global energy supply, Energy 31 (2006) 2235–2251.
[8] T.P. Wright, Factors affecting the cost of airplanes, J. Aeronaut. Sci. 3 (1936) 122–128.
[9] K.J. Arrow, The economic implications of learning by doing, Rev. Econ. Stud. 29 (1962) 155–173.
[10] N. Rosenberg, Inside the Black Box: Technology and Economics, Cambridge University Press, Cambridge, UK, 1982.
[11] B.A. Lundvall, Innovation as an interactive process: from user–producer interaction to the national system of innovation, in: G. Dosi, C. Freeman, R. Nelson, G. Silverberg, L. Soete (Eds.), Technical Change and Economic Theory, Pinter, London, UK, 1988, pp. 349–369.
[12] J.M. Utterback, Mastering the Dynamics of Innovation, Harvard Business School Press, Boston, MA, USA, 1994.
[13] R. Garud, On the distinction between know-how, know-why and know-what, Adv. Strateg. Manage. 14 (1997) 81–101.
[14] A. Grübler, Technology and Global Change, Cambridge University Press, Cambridge, UK, 1998.
[15] A. Grubler, N. Nakicenovic, D.G. Victor, Dynamics of energy technologies and global change, Energy Policy 27 (1999) 247–280.
[16] M.A. Lapré, A.S. Mukherjee, L.N. Van Wassenhove, Behind the learning curve: linking learning activities to waste reduction, Manag. Sci. 46 (2000) 597–611.
[17] L.M. Kamp, Learning in wind turbine development, a comparison between the Netherlands and Denmark, Ph.D. Thesis, Science, Technology and Society, Copernicus Institute, Utrecht University, Utrecht, the Netherlands, 2002.
[18] H.M. Junginger, Learning in renewable energy technology development, Ph.D. Thesis, Science, Technology and Society, Copernicus Institute, Utrecht University, Utrecht, the Netherlands, 2005.
[19] M. Junginger, E. De Visser, K.J.K. Hjort-Gregersen, R. Raven, A. Faaij, W. Turkenburg, Technological learning in bioenergy systems, Energy Policy 34 (2006) 4024–4041.
[20] L. Neij, Dynamics of energy systems, Ph.D. Thesis, Lund University, Lund, Sweden, 1999.
[21] M. Junginger, A. Faaij, W.C. Turkenburg, Cost reduction prospects for offshore wind farms, Wind Eng. 28 (2004) 97–118.
[22] R.E. Albright, What can past technology tell us about the future, Technol. Forecast. Social Change 69 (2002) 443–464.
[23] D.P. Van Vuuren, B. De Vries, B. Eickhout, T. Kram, Responses to technology and taxes in a simulated world, Energy Econ. 26 (2004) 579–601.
[24] J. Köhler, M. Grubb, D. Popp, O. Edenhofer, The transition to endogenous technical change in climate–economy models: a technical overview to the innovation modeling comparison project, Energy J. 18 (2006) 17–55.
[25] J.M. Dutton, A. Thomas, Treating progress functions as a managerial opportunity, Acad. Manage. Rev. 9 (1984) 235–247.
[26] A. McDonald, L. Schrattenholzer, Learning rates for energy technologies, Energy Policy 29 (2001) 255–261.
[27] M. Junginger, A. Faaij, W.C. Turkenburg, Global experience curves for wind farms, Energy Policy 33 (2005) 133–150.
[28] L. Neij, Cost dynamics of wind power, Energy 24 (1999) 375–389.
[29] B.C.C. Van der Zwaan, A. Seebregts, Endogenous learning in climate–energy–economic models — an inventory of key uncertainties, Int. J. Energy Technol. Policy 2 (2004) 130–141.
[30] A.D. Sagar, B. Van der Zwaan, Technological innovation in the energy sector: R&D, deployment, and learning-by-doing, Energy Policy 34 (2006) 2601–2608.
[31] B. Van der Zwaan, A. Rabl, Prospects for PV: a learning curve analysis, Sol. Energy 74 (2003) 19–31.

[32] W.P. Hirschman, M. Schmela, Silicon shortage — so what! Market survey on cell and module production 2005, Photon International March, 2006, pp. 100–125.
[33] L. Neij, P. Dannemand Andersen, M. Durstewitz, P. Helby, M. Hoppe-Kilpper, P.E. Morhorst, Experience Curves: A Tool for Energy Policy Assessment (EXTOOL), Final Report, Lund, Sweden, 2003.
[34] G.J. Schaeffer, E.A. Alsema, A. Seebregts, L. Beurskens, H. De Moor, W.G.J.H.M. Van Sark, M. Durstewitz, M. Perrin, P. Boulanger, H. Laukamp, C. Zuccaro, Learning from the sun: analysis of the use of experience curves for energy policy purposes: the case of photovoltaic power, Energy research Centre of the Netherlands (ECN), Petten, the Netherlands, Report ECN-C-04-035, 2004.
[35] A. Alchian, Reliability of progress curves in airframe production, Econometrica 31 (1963) 679–693.
[36] Van Sark, W.G.J.H.M., Alsema, E.A., Junginger, H.M., De Moor, H.H.C., Schaeffer, G.J. Accuracy of progress ratios determined from experience curves: the case of photovoltaic technology development, Prog. Photovol. Res. Appl., in press.
[37] P.R. Bevington, Data Reduction and Error Analysis for the Physical Sciences, McGraw-Hill, New York, NY, USA, 1969.
[38] K. Levenberg, A method for the solution of certain nonlinear problems in least squares, Q. Appl. Math. 2 (1944) 164–168.
[39] D.W. Marquardt, An algorithm for least-squares estimation of nonlinear parameters, J. Soc. Ind. Appl. Math. 11 (1963) 431–441.
[40] M. Ledvij, Curve fitting made easy, Ind. Phys. 9 (2003) 24–27.
[41] J. Goldemberg, The evolution of ethanol costs in Brazil, Energy Policy 24 (1996) 1127–1128.
[42] J. Goldemberg, S.T. Coelho, P.M. Nastari, O. Lucon, Ethanol learning curve—the Brazilian experience, Biomass Bioenergy 26 (2004) 301–304.
[43] J. Goldemberg, S.T. Coelho, O. Lucon, How adequate policies can push renewables, Energy Policy 32 (2004) 1141–1146.
[44] J.R. Moreira, J. Goldemberg, The alcohol program, Energy Policy 27 (1999) 229–245.
[45] J.D. Van den Wall Bake, Cane as Key in Brazilian Ethanol Industry — Understanding Cost Reductions Through an Experience Curve Approach, M.Sc. Thesis, Science, Technology and Society, Copernicus Institute, Utrecht, University, Utrecht, 2006.
[46] D. Poponi, Analysis of diffusion paths for photovoltaic technology based on experience curves, Sol. Energy 74 (2003) 331–340.
[47] H.H.C. De Moor, G.J. Schaeffer, A.J. Seebregts, L.W.M. Beurskens, M. Durstewitz, E.A. Alsema, W.G.J.H.M. Van Sark, H. Laukamp, P. Boulanger, C. Zuccaro, Experience curve approach for more effective policy instruments, 3rd World Conference on Photovoltaic Energy Conversion, WCPEC-3, Osaka, Japan, 2003, pp. 2624–2627.
[48] G.J. Schaeffer, H.H.C. De Moor, Learning in PV: trends and future prospects, in: W. Hoffmann, J.-L. Bal, H. Ossenbrink, W. Palz, P. Helm (Eds.), Nineteenth European Photovoltaic Solar Energy Conference, WIP, Munich, 2004, pp. 3415–3418.
[49] A. Masini, P. Frankl, Forecasting the diffusion of photovoltaic systems in southern Europe: a learning curve approach, Technol. Forecast. Social Change 70 (2002) 39–65.
[50] C. Harmon, Experience Curves for Photovoltaic Technology, IIASA, Laxenburg, Austria, Report IR-00-014, 2000.
[51] V. Parente, J. Goldemberg, R. Zilles, Comments on experience curves for PV modules, Prog. Photovol. Res. Appl. 10 (2002) 571–574.
[52] Maycock, P. PV News, several issues over the years 1995–2002.
[53] Strategies Unlimited: Photovoltaic Five-Year Market Forecast 2002–2007, Mountain View, CA, USA, Report PM-52, 2003.
[54] G.F. Nemet, Beyond the learning curve: factors influencing cost reductions in photovoltaics, Energy Policy 34 (2006) 3218–3232.

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