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Technology Learning Curves for Energy Policy Support

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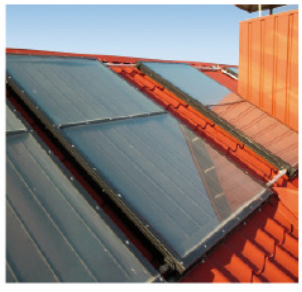




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1. Context

The European Commission's Joint Research Centre and the Energy Research Centre of the Netherlands (ECN) organised an expert workshop on 'Learning Curves for Policy Support' in Amsterdam on 8 March 2012. It aimed to assess the challenges in the application of the two-factor learning curve, or alternative solutions in supporting policy decision making in the framework of the European Strategic Energy Technology Plan, and explored options for improvement. The workshop gathered distinguished experts in the field of scientific research on learning curves and policy researchers from the European Commission and ECN to assess the challenges in the application of the two-factor-learning curve, or alternative solutions in supporting policy decision making, and to provide options for improvement.

The key discussion topics were:

1. Is the concept of the Two-Factor-Learning-Curve, i.e. the linkage of the knowledge stock to technology costs, a suitable approach? Or is it recommended to apply an (improved) One-Factor-Learning-Curve?
2. Do uncertainties in parameters (i.e. learning rates) impede a meaningful result?
3. Do uncertainties in data (e.g. R&D investments) impede a meaningful result?
4. How best to include learning in modelling?

A list of the participants of the workshop, the agenda and the background material (elaborating on each of the four key discussion topics) can be found in the annex of this report.

This paper forms the summary of outcomes from the workshop. Due to the very different nature of the One-Factor-Learning concept and the Two-Factor-Learning concept, these are discussed in separate parts. In each of these parts the context and the methodology are introduced, methodological and data challenges are described and the problems associated with the application of the concept in models is discussed.

2. Introduction

Innovation is an important driver of growth in all economic sectors and is therefore the focal point of a Flagship Initiative under the 'Europe 2020' strategy. In the energy sector, the successful research, development and deployment of innovative technologies is a cornerstone of the transition towards a low-carbon economy that aims at reductions of greenhouse gas emissions in the order of at least 80% by the year 2050 (see e.g. European Commission, 2011; IEA, 2010) .

A mature system such as the energy sector, however, is prone to a lock-in to current technologies. The lock-in effect leads to path dependency in widely deployed, mature technologies that benefit from the previously accumulated knowledge and infrastructure, and therefore constitutes a main barrier to the uptake of competing innovative technologies. This barrier becomes apparent when innovative solutions require significant start-up investments ('learning investments') in technology and infrastructure to compete against relevant past expenditures that have already been amortized and whose influence cannot be reversed easily. In addition to the lock-in effect, externalities in the energy sector are still only partially internalised, thereby creating an additional disadvantage to low-carbon technologies compared to the mostly fossil-fuel based current energy system. Hence, Jaffe et al. (2005) describe this situation as 'a tale of two market failures' that require both technology policy and environmental policy.

The European Union has reacted to this need of public intervention. For example, European policy has supported the deployment of renewable energies for more than two decades, starting with the 1997 White Paper and followed by sectoral targets for renewable electricity and transport biofuels. In 2009, the European Union introduced a renewable energy target for the year 2020 as part of its Energy Policy for Europe (European Commission, 2007a). By then, 20% of the Community's gross final consumption of energy shall be produced from renewable sources (EU, 2009)[1]. At the same time, the European Emission Trading Scheme provides economic incentives for the reduction of GHG emissions for sectors covered under this instrument. These 'market-pull' policies are complemented by 'technology-push' policies that foster research and development. The European Strategic Energy Technology Plan (SET-Plan; European Commission, 2007b; also: European Commission, 2009) aims at supporting Research and Development (R&D) and the market uptake of low-carbon energy technologies.

The concept of learning curves is at the foundation of the 'push' and 'pull' policy approach of the European Union, whereby policy interventions are directed at encouraging the economic evolution of the technologies along their development curve. Learning curves express the hypothesis that the cost of a technology decreases with a constant fraction with every doubling of installed capacity or exercised activity (Wene, 2000; Schoots et al., 2008). Each time a unit of a particular technology (e.g. a wind turbine) is produced, some learning accumulates which leads to cheaper production of the next unit of that technology. We can distinguish learning curves which are based on

[1] Recently, the European Commission published a Communication that outlines possible policy options for renewable energies beyond 2020 (European Commission, 2012).

costs, and experience curves which are based on prices and may include market effects like price umbrellas.

Policy interventions aimed at increasing the competitiveness of entrant technologies by increasing their installed capacity, assume that costs will decrease as accumulated production increases, leading to the technology being increasingly cost competitive in the marketplace. [2]

Historical observations of technology cost development and understanding the mechanisms behind these developments such as research efforts, learning-by-doing and economies-of-scale are essential when trying to understand possible future paths of technology cost reductions, and how these are related to projected technology developments. As EC policy makers attempt to set polices today to convert the EU into a low-emission society, EC policies are constructed on the basis of expected future emissions, which are calculated based on a future energy mix that depends heavily on the future costs of energy producing technologies.

Hence, using the learning curve concept seems a suitable tool when assessing the impact of one technology deployment policy option compared with another. To this end, many economic and technological modelling tools include an endogenous mechanism to simulate the dynamic evolution of technologies.

Whereas the use of the learning concept as a conceptual tool in models is widely accepted, it becomes significantly more difficult when applied in order to assess the effectiveness of different components of an innovation policy – i.e. to evaluate the effects of a technology push versus a market pull mechanism.

A first attempt to quantify the costs and benefits of increasing energy technology R&D investments has been undertaken in the context of the SET-Plan Information System (Wiesenthal et al., 2012a). It applies a methodology using the concept of Two-Factor-Learning, which quantitatively links trends in technology costs to both accumulated R&D investments and production volumes. The impact of the latter on the energy sector is then simulated in a consistent manner with the POLES global energy model. On this basis, two scenarios that both fulfil the EU's 2020 energy and climate objectives and differ only in their R&D investment levels have been compared. The results of this work indicate that the reduced technology costs induced by additional R&D investments allow support policies for renewables and carbon values to be lowered, and the cumulative (discounted) benefit of the accelerated research efforts are positive in the long term.

At the same time, this work points out a number of challenges on both the methodology and the underlying data, which significantly influence the results. In order to further develop this line of assessment in support of the SET-Plan, the present workshop and this summary paper address these challenges in a structured manner, and propose conclusions on how to move forward in future assessments.

[2] This is the indirect effect of these policy interventions. Obviously, there is also a direct effect, because increasing the installed capacity immediately lowers the emissions of the energy system. However, the level of financial support is usually higher than the marginal cost of emissions abatement (as indicated by e.g. CO_2 emissions allowance prices), hence the rationale for the policy intervention is usually also the indirect effect described here.

To this end, it summarises the methodological background of both the One-Factor and the Two-Factor-Learning Curve concepts and looks into possibilities for further refining them. For both concepts it looks into methodological challenges, uncertainties in parameters and data availability. It also addresses the question on how to include the learning concept in energy system models, before it concludes.

3. The learning concept

Among the first to describe the concept of learning was Wright (1936). In his paper, Wright observes a uniform decrease in the number of direct labour hours required to produce an airframe for each doubling of the cumulative production of the plant under consideration. Improvements in performance, productivity and/or cost of a technology in relation to the accumulation of experience are often referred to as 'learning by doing'. Figure 1 shows a learning curve with a learning rate of 20%. The blue line indicates the uniformly decreasing costs of the entrant technology, the red line the cost level of the incumbent technologies that are competitive in the market. The basis for learning curves has been observed in careful empirical studies but its theoretical foundations are restricted to a much narrower interpretation encompassing only labour costs and within individual firms (Arrow, 1962).

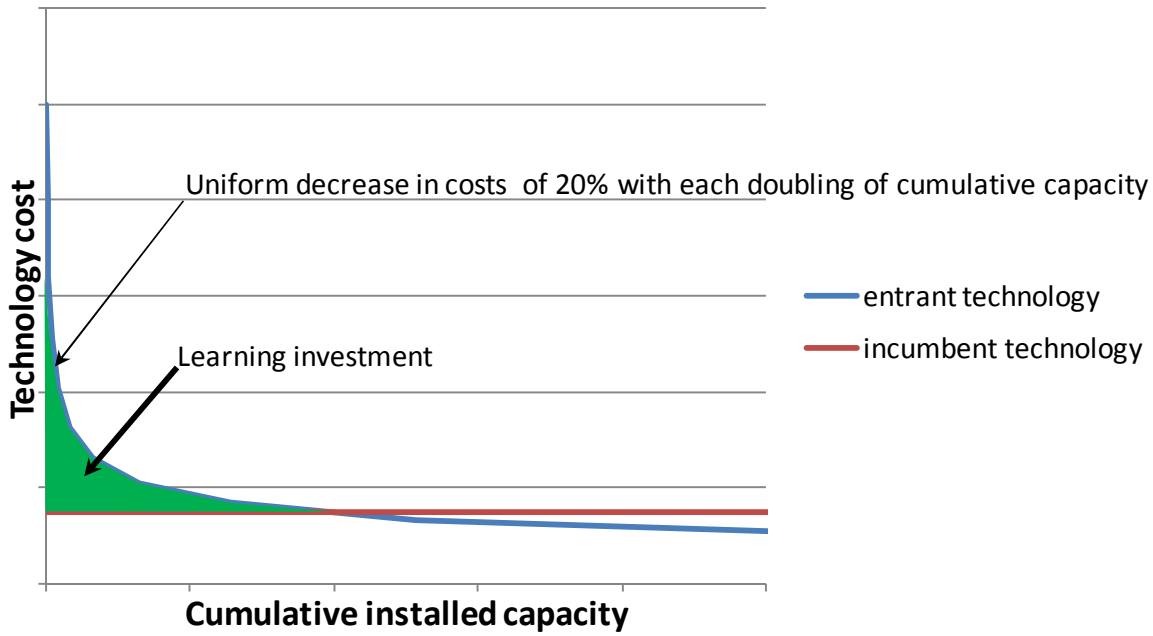

Figure 1 - Cost development of an entrant and an incumbent technology.
Source: own work

The concept of learning curves illustrates the benefit of early investment and policy interventions in emerging technologies as well as the need for an initial market in order to allow emerging technologies to accelerate their cost reductions and reach cost competitiveness with existing technologies in the market earlier. In this respect, learning curves are often used to extrapolate past cost reductions to future cumulative production levels and provide an indication of the so-called 'learning investments', i.e. the additional investments needed for deployment of the entrant technology while learning effects cover the gap between the costs of the entrant technology and the cost level of incumbent technologies. In Figure 1 the learning investment is indicated by the green shaded area.

At the same time, several weaknesses in quantifying and using learning curves have been identified. The costs of a given technology are composed of many factors, material

costs, labour costs, technology costs, not all of which are exposed to cost reductions through learning-by-doing. Some cost components may increase.

The observed cost reductions are the result of a multitude of different cost-reducing processes (see e.g. Kahouli-Brahmi, 2008), including learning by doing (Arrow, 1962), learning by researching (Cohen and Levinthal, 1989), learning by using (Rosenberg, 1982), learning by scaling (Sahal, 1985) and learning by copying (i.e. knowledge spillovers) (Sagar and van der Zwaan, 2006).

The effect of these underlying factors can not be easily disentangled, thus masking the diverse drivers of technology costs. The Two-Factor-Learning Curve (TFLC) approach tries exactly to do this – in order to better assess the impact of diverse cost-reducing drivers, it separates out the effects of learning-by-doing and learning-by-searching.

In addition to the factors sketched out above, market prices of raw materials and components produced by third parties may play an important role in the technology's cost dynamics. In order to better address this, Ferioli et al. (2009) proposed to split up the technology costs into components and allocating the appropriate learning effect and learning rate to each cost component.

The use of learning curves has been criticised (see for example Neij, 2003a; Nemet, 2006; Nordhaus, 2009; Holmes, 2010) due to the uncertainties associated to the lack and treatment of data, and the aggregated approach to innovation. In particular, the TFLC is considered problematic from a methodological viewpoint as well as from a data point of view. The use of learning curves in models to assess future technology dynamics bears a number of problems that may lead to an overestimation of the learning effect. In conclusion, the critique articulates the need of complementary tools when analysing the dynamics of energy systems. Learning curves, at least one-factor-learning curves, are a suitable tool but need to be set into context as they extrapolate an observed phenomenon without being able to analyse its drivers in detail, or provide projections with great accuracy.

4. The One Factor Learning Curve

4.1 Basic methodology

The One Factor Learning Curve (OLFC) depicted in Equation 1 relates the unit cost development of a technology to the evolution of one factor, the accumulated learning, classically represented by accumulated production. It is illustrated by plotting a reduction in technology costs against its accumulated production. For example in the power generation sector it can be represented by a plot of specific installation costs versus the accumulated installed capacity of the involved technology. The unit cost development observed with one-factor learning curves – in which costs reduce by a constant fraction for each doubling of cumulative production – can be described by a power law:

$$C_{t,y} = mQ_{t,y}^{-\varepsilon} \qquad \textit{(Equation 1)}$$

With C = Costs of unit production (€/W)
Q = Cumulative Production (W)
ε = Elasticity of learning (learning index)
m = normalisation parameter with respect to initial conditions
t = Technology
y = Period (year)

The OFLC benefits from relatively easily accessible data. Investment costs and production (or installation) volumes are often well recorded compared to other underlying cost drivers, and thus reliable learning curves can be determined for economic modelling purposes.

The power law behavior enables plotting of learning curves as a straight line on a double-logarithmic scale. This visualization is chosen in Figure 2. Despite some annual fluctuations, the figure shows a good match between the real cost data of PV and the cumulative module shipments. Moreover, extrapolating the line further gives a rough indication about the capacity at which a certain cost level would be reached. Figure 2 also indicates the learning investment required to reach a cost level of 1 €/W_p.

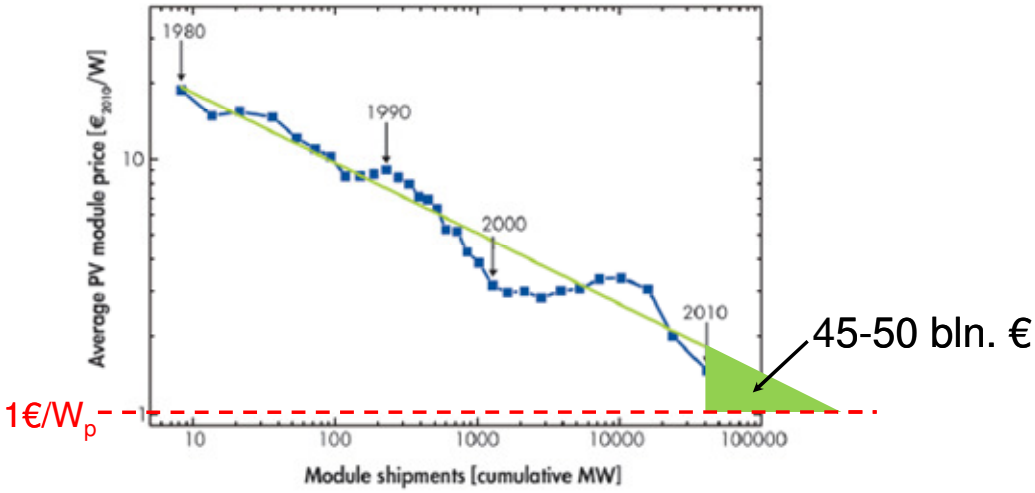

Figure 2: Learning curve for PV indicating at what shipment level the costs of 1 €/W_p may be reached and the learning investment required for that goal.
Source: Presentation Robert Kleiburg, ECN, referring to the EU Photovoltaic Technology Platform (2011)

4.2 Improvements to the One-Factor-Learning Concept

For a number of technologies, the learning effect is less evident than for the case of PV shown above, or even non-existing e.g. for hydrogen production or gas pipelines (Schoots et al., 2008; van der Zwaan et al., 2011). In other cases, the OFLC can be constructed but the statistical significance is low, and annual fluctuations in costs are high. Also, net cost increases may be observed when e.g. market tightness and commodity price increases offset the cost-reducing technology learning effects.

Hence, a proposed improvement to the OFLC is to split the total cost into more of its underlying components, and analyse each cost separately. In this multi-component learning analysis (see Ferioli et al., 2009; van der Zwaan et al., 2011) some cost components experience learning (e.g. the production process) and some do not (e.g. labour costs and material costs). This leads to only a fraction of the total cost experiencing learning effects.

$$C(x) = \alpha C(x_0)\left(\frac{x}{x_0}\right)^{-L} + (1-\alpha)C(x_0) \qquad \textit{(Equation 2)}$$

With
x : cumulative output
x_0 : cumulative output at t=0
$C(x)$: cost at cumulative output
L : learning parameter
$LR = 1 - 2^{-L}$: learning rate
α : cost share of learning component at t=0

If historical costs are analysed on this partial-learning basis the analysis could derive vastly different learning rates and results and achieve a better match with statistical data as shown for the case of gas turbines in Figure 3, where it is assumed that only 80% of the technology is exposed to learning (Ferioli et al., 2009). Moreover, applying

technology learning to only a part of the total costs will have an important impact in technology forecasts or energy scenarios (see illustration in Figure 3).

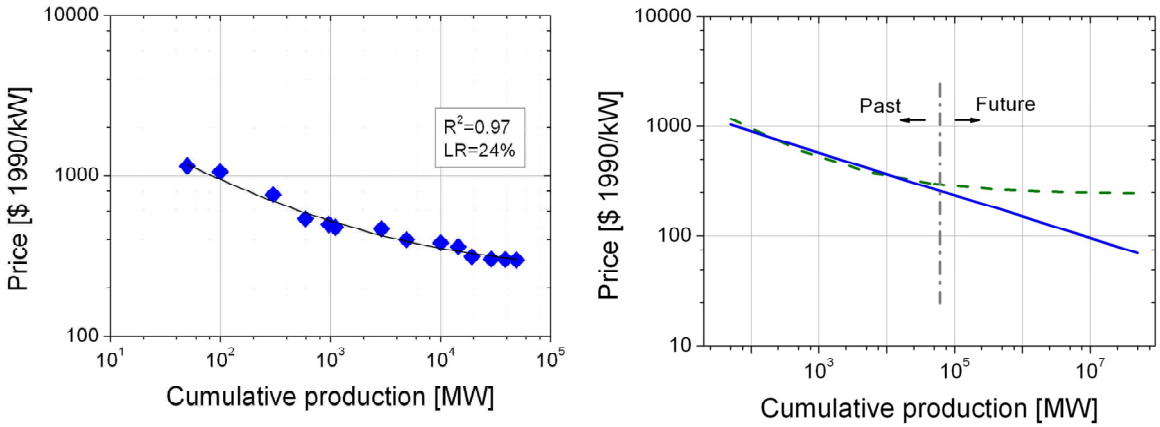

Figure 3: Multi-component learning for gas turbines (left) and implications for future predictions

Source: Ferioli et al., 2009; taken from the presentation of B. van der Zwaan, ECN

The fraction of the total cost that learns is also an aggregation of the costs of the individual components of the technology. Each component can have a different learning rate. One approach is to analyse the learning of these components separately, however separate production data and particularly costs are not easily found.

Technology learning occurs not just vis-à-vis its investment cost, but in many aspects of a technology such as conversion efficiency, maintenance costs, safety features, reliability etc. All drivers in a business are geared towards profit maximisation, and lowest investment cost does not always equate to profit maximisation. For example, investment costs have been rising recently for coal power stations as they are being designed with shortened 'ramp-up' and spinning times which allow greater plant flexibility, even if Yeh and Rubin (2007) estimate a learning rate of 6% for coal power plants. Hence, other indicators than the specific investment costs may be more appropriate representations of learning outputs, such as product functionality (Watanabe et al., 2009, 2011), input costs, or levelised cost of electricity for a power generation technology. For some technologies (e.g. mobile phones) it may be easier to quantify the functionality than for other technologies. For certain technologies innovation is not taking place on the technology supply side (i.e. production costs), but on the demand side (i.e. for what purpose end-users are using a technology). In ammonia production (where energy costs are a significant share of the total costs) investment cost is highly scattered but there is a very good fit of the experience curve with the energy input to production.

Some research applying a cybernetic theory indicates that technology learning can be seen as a stable controlled property of an operationally closed system in a competitive environment (Wene, 2007, 2011). The observed clustering for learning rate around 20% (see Figure 4) is a footprint of the property. If a closed system is in charge of all its operations this means the stability of extrapolation can be trusted (as for the learning rate of PV). If the observed learning rate deviates substantially from the 'eigenvalue' of 20%, one would need to look for the influence of external factors, e.g. what is the role of

public R&D, radical innovations, regulations, production scale, technology cross-over[3] and spill over. For example, the heavy regulation in nuclear power would explain the poor learning curve of this technology with regard to costs; here, possible benefits from learning effects in certain components are balanced by rising costs for increasingly stringent safety measures. The observed learning rates for wind turbines below 20% can be explained by the fact that turbines are only part of the total technology; when Junginger et al. (2010) started to look at global learning for complete wind parks, learning rates closer to the basic learning mode at 20% were found.

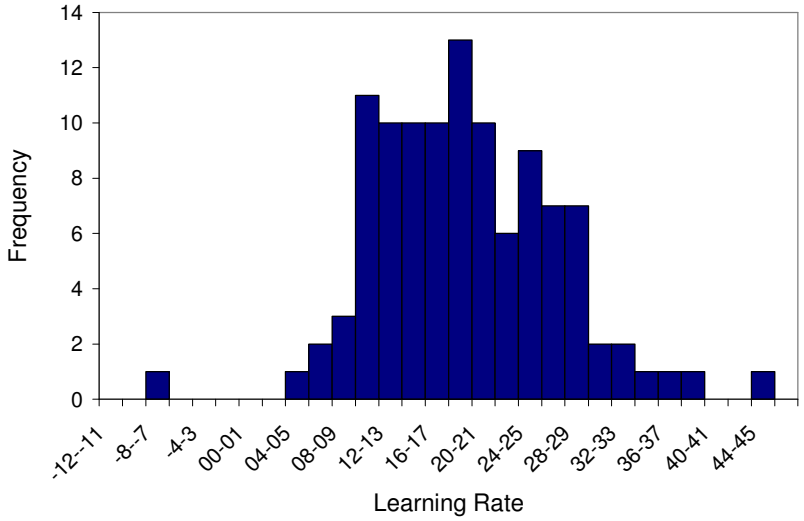

Figure 4: Frequency distribution of learning rates (in firms and by costs)
Source: Dutton and Thomas, 1984; taken from the presentation of C.O. Wene

While all refinements to the OFLC described above may help in refining the traditional learning concept that masks underlying trends, they may cause problems with data availability associated to quantifying all the parts of the total cost. Relevant data challenges are discussed in more detail in the next section.

4.3 Challenges: data and calibration of learning rates

Learning rates vary significantly across various studies and data sets. One major issue in using learning curves is correctly treating the historical data to calculate a learning rate. Depending on the spread of the data, it is possible to calculate different learning rates by changing the starting and ending point of the analysis and the choice of including or excluding outliers. For example, a 30-year data set of costs and experience data has 253 possible periods of at least 10 years, which one could use to calculate learning rates (Nemet, 2009). Performing these calculations for individual energy technologies shows a distribution of learning rates within a single technology that is nearly as broad as that across technologies (McDonald and Schrattenholzer, 2001). Others show learning rates becoming negative in early periods before increasing (Rubin et al., 2007). Historical datasets for new technologies may be very short and thus introduce greater uncertainty due to a small sample size. Care must be taken to treat the data in a way that produces a representative learning rate.

[3] Technology cross-over refers to technology components that are taken over from other sectors.

At the same time, it is important to separate the effects of learning from other factors to the extent possible. At the least, it is preferable to use cost data instead of price data. Ideally, factors such as commodity prices would be removed by correcting observed data with a commodity price index (see van der Zwaan et al., 2011). Furthermore economies-of-scale should be excluded too as these are based on a different cost reduction mechanism and render data from different manufacturers incomparable (Schoots et al., 2010)

The learning concept quantifies an observed relationship without being able to analytically disaggregate the individual driving factors– i.e. the shares caused by learning by searching, learning by doing, economies of scale etc. However, the contribution of each of the underlying cost reducing factors is likely to vary over time, depending on the phase of the innovation process. These different phases in the historical cost development of the technology may lead to calculating different learning rates for the different phases, which would differ from a learning rate for the whole data set (Wene, 2000). This implies that learning rates may change over time. Rivera-Tinoco et al. (2012) show for the case of Solid Oxide Fuel Cells (SOFCs, see Figure 5) that the stage of technological innovation and corresponding data set one applies the learning curve methodology to, has a large influence on cost development. Again, as a result, the value of the learning rate can vary significantly.

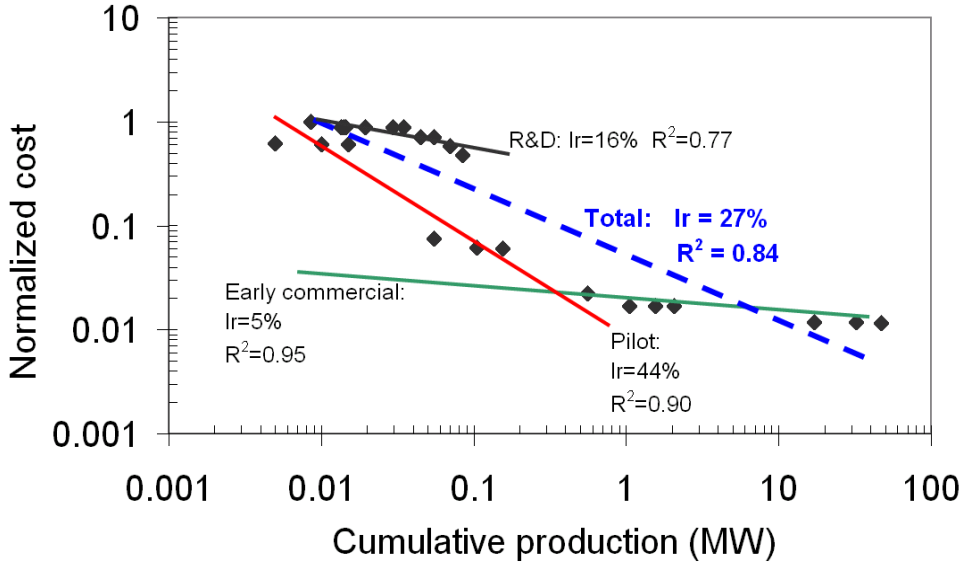

Figure 5: Learning of fuel cells (SOFCs) broken down by phases

Source: Rivera-Tinoco et al., 2012; taken from the presentation of B. van der Zwaan, ECN

4.4 Implementation in energy system models

Despite some uncertainties related to data, the One-Factor-Learning-Curve has proven to be a useful framework for following empirically observed technology cost evolutions. Once a learning rate has been calculated the interest for the analyst is to use this learning rate to model future cost developments. Implementation of learning rates in a modelling environment in order to endogenously capture some likely future technology dynamics raises, however, several questions:

- Is there a limit to technology learning?

Should the future cost be limited by a floor cost, or an absolute lower limit to production costs? Such an implementation has the advantage of reducing the likelihood of overestimating the technology cost reduction potentials (e.g. Rout et al., 2009). At the same time, however, floor costs may be conservative estimates and may hide opportunities and conserve status quo.

If floor costs were implemented, how should they be determined? Bottom-up engineering estimates are based on current knowledge and state of the technology, and therefore discount possible breakthroughs and therefore tend to be too pessimistic.

- Costs or prices?

  A learning curve describes the development of production costs, as a function of accumulated produced volume. Actual diffusion of technologies is however determined by market prices. Prices can differ strongly from the actual production costs. This could be accounted for by modelling the supply and demand in the market. It also leads to the problem of price data which is sometimes used in modelling (as it can be easier to collect) not equating to cost data (which may be market sensitive and difficult to obtain). Still, cost data may include components that are purchased from third parties and therefore include price effects as well.

- Do learning rates vary over time?

  The concept of different cost development phases discussed above leads to the issue of how to use learning curves when there are dramatic changes in technology in itself, such as breakthroughs – i.e. radical innovations –, or in a technology's market circumstances, such as the appearance of a competing technology. This variation applies both to determining the proper learning rate from the historical data and to the effect of possible future breakthroughs, leading to under or over-estimations of future costs.

  Should breakthroughs be considered in the current learning rate? Or does a breakthrough represent a new technology, so the learning rate has to be considered reset immediately after a breakthrough? If breakthroughs cannot be captured by the learning concept, they may need to be introduced through varying exogenous assumptions, leading to diverse sensitivity cases.

- Selection of scenarios

  One of the most important uses and justifications for including learning curves in models is to ensure internal consistency when comparing between scenarios. The greater benefit is realised not in the construction of the first scenario, but with the following scenarios. Hence, if one assumes in a certain scenario an X-fold increase of e.g. R&D investments, it is questionable whether the same learning rate as in the baseline case can be applied.

- How to define the system boundaries?

- Global or regional?

  A very important question to answer is whether technology learning is a global phenomenon or whether learning develops at different rates due to regional specific factors. Answering this question will also have an important impact on the choice of models (global vs. regional) that are suited for endogenously simulating learning.

  In general, a global approach is advised since the technology of e.g. a wind turbine is the same in all countries, therefore leading to a globally defined learning rate. In the global marketplace for some technologies there can be development and production in one region and installation in another (e.g. wind turbines produced in Denmark installed in Asian countries). Cost components relying on local skills and or embedded in local institutions, such as the installation of PV systems on buildings, may not find its way to other regions. This further blurs the regional differences and complicates data collection.

  At the same time, clustering of industries or companies could drive faster innovation at specific sites leading to regional differences in learning rates. Fuel ethanol from sugarcane in Brazil between (1975-1995) can be named as one example. However, any regional diversity in technology economic and technical performance is likely to be short lived as the superior technology will either conquer or be imitated and thus disperse to all regions.

- Sectoral boundaries

  Improvements within a certain technology often benefit from advances made in other fields, such as materials research or the benefits of military aircraft research that was fruitful for the development of the combined cycle gas turbine. Hence, it is important to set the appropriate system boundaries in order to consider spill-over effects across sectors (Martinsen, 2011). Depending on the stage of the innovation chain, the system boundaries (as well as the regional boundaries, see above) may change as illustrated below in Figure 6.

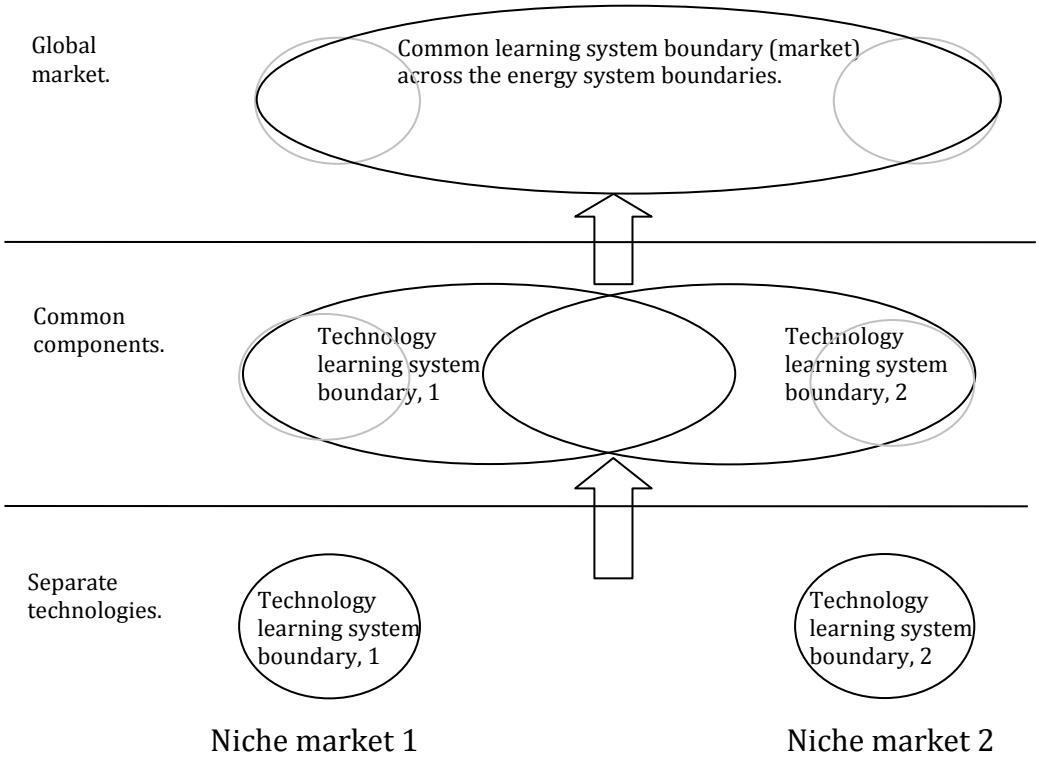

Figure 6: A stylistic view of three stages in the system boundary for technology learning
Adapted from: Martinsen, 2011

As for many model-based scenario assessments, uncertainty could be understood by a sensitivity analysis. Although a sensitivity analysis is most useful for characterizing the sources of variation in model outcomes when those sources are poorly understood, in this case we can confidently predict from the existing literature that results will be sensitive to assumptions on learning rates. A sensitivity analysis could identify the technologies for which the uncertainty – and therefore spread – in future learning rates strongly influence preference of one policy over another. Also with multi-factor learning analysis a sensitivity analysis may highlight which factors are more uncertain.

5. The Two-Factor-Learning Curve: introducing the explicit representation of R&D

One of the strengths of the One-Factor-Learning Curve is that it simplifies cost dynamics because it groups several underlying drivers of cost reduction in one factor that matches empirical data.

At the same time, this high level of aggregation is a major criticism of the One-Factor-Learning Concept as it does not allow the analyst to quantitatively associate the observed cost reductions to individual drivers such as research and learning-by-doing. Moreover, this makes it impossible to provide a clear quantitative assessment of the impact of a policy option that addresses just one of these factors, such as R&D investments.

Hence, a split of the OFLC into a Two-Factor-Learning Curve (TFLC) has been undertaken by Kouvaritakis et al. (2000). In the following, the methodology behind TFLC is described. Then follows further elaboration on methodological and data issues, based on the discussions held during the expert workshop.

5.1 Methodology

The Two-Factor-Learning Curve disentangles two of the most important learning factors: learning by doing and learning by searching[4]. The latter describes the relationship between an accumulated knowledge stock and production costs. The TFLC can be described as follows for a given technology t and time period y

$$C_{t,y} = aQ_{t,y}^{-\alpha} KS_{t,y}^{-\beta} \qquad \textbf{(Equation 3)}$$

With C = Costs of unit production, €/W
Q = Cumulative Production, W
KS = Knowledge stock (here: approximated through R&D investments, €)
α = Elasticity of learning by doing
β = Elasticity of learning by researching
a = normalisation parameter with respect to initial conditions

5.2 Methodological challenges of the Two-Factor-Learning Curve

5.2.1 Interdependence between different factors

Learning by doing and learning by researching effects are linked, they depend on each other and occur simultaneously. A robust result from the innovation literature is that it

[4] These may not be the most important factors determining costs. That depends on which components dominate the cost structure of a technology. For technologies where the costs are mostly determined by raw materials costs, such as steel, costs are determined by market prices and not by learning effects. Also the contribution from learning by researching and learning by doing may not be equal, i.e. a technology may be further down the learning by researching curve than the learning by doing curve or learning by searching may apply to different cost components (and thus share) than learning by doing.

is the interaction of R&D and production related effects like learning by doing that produce innovation (Grübler, Nakicenovic et al., 1999).
An illustration of the importance of combining several factors in order to successfully develop and deploy a technology comes from the early development of wind turbines for wind electricity (taken from the input note from L. Neij):

> *Other elements in the innovation chain can be more important than R&D investments; R&D is often fundamental but not enough. One example that illustrates this is the early investments in wind energy. In some countries like Germany and Sweden, wind energy innovation was initially supported through RD&D only and the innovation process was envisioned to be linear. However, the RD&D funding alone did not bring about any commercial turbines. Other countries, like Denmark and the US, started to support (potential) users and market formation already in the late 1970s and early 1980s, allowing small and medium sized enterprises and individuals to attend subsidy programs. The broad user-oriented initiatives came to contribute to important learning-by-using and essential feed-back to the development of the wind turbine. The experience supported technology development, the upscale of wind turbines and considerable cost reductions. The wind energy case shows that the design of resources mobilization is of importance. Countries like Germany and the US initially spent enormous resources on RD&D which only resulted in a few commercial wind turbines; whereas Denmark spent much less resources on RD&D but did effectively support the innovation path of wind turbines. The initial RD&D expenditures in Denmark has been calculated to approximately 47 M EUR until year 1990 whereas RD&D expenditures in Germany during the same time period was 227 M EUR (Neij et al. 2003b). In the US, early RD&D expenditures have been calculated to be more than 20 times as high as the Danish RD&D expenditures (Heymann, 1998). Thus, it was not the resource mobilization through early RD&D that was the major driver for the development and deployment of wind turbines.*

Hence, learning by doing and learning by searching cannot be satisfactorily separated. And certainly, the one factor cannot substitute the other – as would be allowed by the TFLC. One possible improvement would be to introduce an interaction term (LbD x LbS) that would account for this synergy.

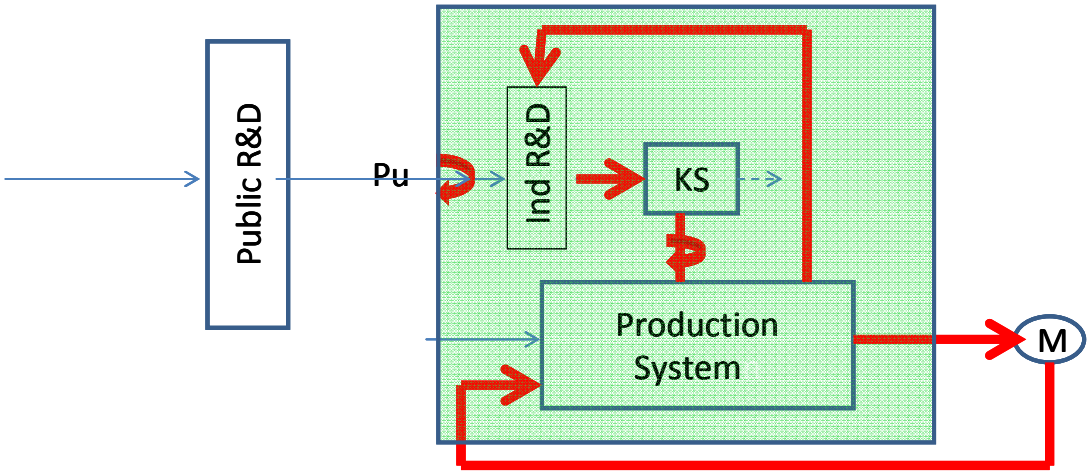

Figure 7: Strongly interconnected learning system
Source: Presentation Clas-Otto Wene

Cybernetic theory accounts for this interaction between R&D and deployment. It regards technology learning as a stable controlled property of a closed system in a competitive environment (Wene, 2007, 2011; van der Zwaan et al., 2011). In the cybernetic approach, there are two cycles which are both driven by the cumulative output: (i) the production system feeds the market while the market influences the production system and (ii) the production system triggers more private R&D increases knowledge stock and this in turn influences the production system (see Figure 7). Thus, per the cybernetic approach, it is not possible to distinguish learning-by-doing and learning-by-searching. They do exist and have an impact but it is impossible to actually allocate cost reductions to R&D and production separately. The problem of disentangling learning by-searching and by-doing re-emerges in the open system, because external features, events or processes may govern internal operations. The cybernetic approach avoids this problem, because it considers the learning system to be in full control of all its internal operations. In this case public R&D appears as an external perturbation to which the system adapts, e.g., by moving away from the 20% learning rate of the unperturbed case. However, the cybernetic approach still lacks a clear methodology to calibrate this impact of public R&D on the observed learning curve.

5.2.2 Establishing a quantitative relationship between R&D and technology improvement

As research is an intrinsically random process, attempting to quantify the outcomes of R&D introduces uncertainty in outcomes. One proposal to combat this uncertainty would therefore be to use a stochastic model (such as Prometheus) to assess the impact of R&D.

One way to alleviate this problem may be to distinguish between different types of innovation. Incremental innovations remain well within the boundaries of the existing market and technologies/processes of an organisation, benefitting from the accumulated knowledge and innovation systems built up on the existing energy system

and the existing infrastructure. Unlike for radical or systemic innovations, i.e. innovations that diverge from the current predominant design, one may argue that for the case of incremental innovations the absorption capacity of additional R&D investment already exists, which could imply that the outcome of incremental innovations is more predictable and stands in clearer relation to the inputs into (applied) research. This would then pose the problem of how to deal with radical innovations, i.e. breakthroughs (see also section 4.4).

In general, however, approximating the knowledge by the cumulative R&D investments was considered problematic. There are many complimentary elements of building a knowledge stock, such as collaboration and networking and feedback loops (Grübler, 2012), but those other parts are often harder to measure. Hence, the approximation of the knowledge stock by the cumulative R&D investments disregards improvements in the efficiency of the research being performed. It could be imagined that a research-intense scenario would be accompanied by measures to increase the efficiency of research, through for example the exploitation of synergies between key actors.

Setting the system boundaries is of utmost importance since there are important spillovers from e.g. military or material research into the energy sector (see also section 4.4). This may be captured by assuming that if total economy wide R&D is large you will have more spillovers than if total economy wide R&D is small, even if the industry specific R&D is the same in both cases.

The impact of R&D spending may become less effective once the technology is in an advanced state of development. On the other hand, an increasing market sizes releases increasing funds for R&D. Using cumulative R&D investments explodes knowledge stock which causes a dramatic cost reduction in Equation 3. However, as time progresses and more ways to reduce costs are found, it becomes harder to further reduce costs, i.e. R&D effectiveness changes throughout a technologies life cycle. Given the increasingly difficult search for cost reductions, one may strongly overestimate cost reductions through learning by searching when using cumulative R&D investment. A possible solution is to use R&D investment *intensity* instead. This is the investment on R&D per unit of production. Alternatively, including a quadratic term for R&D stock enables representation of the diminishing returns to investment, which seem to accurately characterize the learning system.

It is also questionable whether it is useful to group public and private R&D within the Knowledge Stock as this presupposes that they both act in a similar manner in driving innovation. This is nevertheless almost certainly not the case, particularly when technology maturity is considered. When considering the system, one perspective is that the industry R&D is actually the one feeding the knowledge stock whereas public R&D seeds the private one. The cybernetic theory of learning therefore proposes to include the private R&D in the "learning system" and consider public R&D as an external perturbation. The benefit of this approach is that public policy can more easily act on public R&D budgets than on private R&D spending. From a policy point of view, the interesting question is the effect of public R&D efforts on learning, i.e., how public R&D expenditures influence OFLC learning rates. Restricting the TFLC to public R&D investments removes many methodological concerns without reducing its usefulness for

policy. Klaassen el al. (2005) analysed the effect of public R&D on wind energy in Denmark, Germany and the UK.

Popp, Santen et al. (2012) have proposed using patent counts as a proxy for knowledge stock rather than R&D budgets, as a patent is a closer indication of innovation and the data is relatively accessible. Also spillovers between technologies can be measured through patents e.g. PV patents have 30% of citations outside of area (Nemet, G. F., in review).

Criticism is not restricted to the proxies used for the knowledge stock but also the output function. The focus of R&D does not necessarily lie on investment costs but on technological improvements such as efficiency, maintenance, safety and other factors, both technological and non-technological. Using investment costs as the sole output of R&D is a distortion, similar to the point made for the OFLC in section 4.2.

5.3 Data challenges

Data on R&D investment is scarce, in particular when a high level of technological disaggregation or private sector investment is needed. In the energy field, the IEA RD&D statistics provides information on energy RD&D budget from its member countries. Despite some related uncertainties that originate from data gaps and differences in the extent to which individual member countries include regional funding, institutional budgets and support to demonstration activities in the data submitted to the IEA (Wiesenthal et al., 2012b), this dataset is a very useful starting point reflecting public R&D investments. Additional public R&D investments at the EU level can be obtained from data on the Research Framework Programmes.

In general, it has been considered that demonstration activities are more strongly associated with the 'learning-by-doing'. Hence, they would not primarily contribute to the knowledge stock, which should focus on R&D only (if at all considering the above criticism). However, the IEA RD&D statistics in theory also cover funding of demonstration activities. In practice, however, most Member States do either not provide data on funds directed towards demonstration or do not display them separately. Hence, data on aggregated public national funds of EU Member States dedicated to demonstration amount to some 9% of the total energy R&D budget only (Wiesenthal et al., 2009). Hence, one can assume that the IEA database largely focuses on research, a hypothesis that is supported by the large similarity of the aggregated EU figures with data from the GBOARD, the latter of which includes R&D only.

Data on corporate R&D expenditure are more difficult to obtain, in particular when focusing on the R&D expenditure by technology (see e.g. Jacquier-Roux and Bourgeois, 2002; De Nigris et al., 2008; van Beeck et al., 2009). Furthermore, even if data were available, attention needs to be paid to the fact that companies may over- or under-estimate them for strategic purposes (Jacquier-Roux and Bourgeois, 2002; Gioria, 2007).

This data scarcity can be explained by a combination of various factors. No regulation obliges private companies to report their R&D investments, unless they are listed on the stock-markets and thus need to present their financial accounting and an annual report. The R&D investments included in these documents, however, are usually not specified

further by field of activity or technology. This missing breakdown by technology poses less of a problem for companies that are specialised in one sector, but constitutes a major challenge when assessing the research efforts of large component suppliers that are major industrial players with many diversified activities. Estimating the parts of research that are relevant to energy, and even more specifically to individual technologies as required for the calibration of the TFLC therefore needs a well-defined approach. To this end, Wiesenthal et al. (2012b) propose a four-step methodology for the estimation of corporate R&D investments at technology level based on a number of proxy indicators. This approach can overcome gaps in existing data by combining publicly available information in a novel way, and has been illustrated and validated for selected low-carbon energy technologies. However, this approach is time-consuming and extending it to cover time-series of many decades may therefore be unrealistic.

All in all, the limited availability of consistent datasets means that elevated uncertainties are associated with the estimation of cumulative historic R&D investments. This makes it difficult to calibrate reliable learning by searching rates.

To remedy this, the use of patents as proposed above may be one option. Also, a restriction to public R&D as explicit indicator, proposed above by the cybernetic approach 5.2.2, would alleviate data concerns. Still, these solutions have their problems too. Manufacturers choose their own policies which may limit some companies' propensity to patent. Double counting as the empirically determined learning curves include the effect of public R&D spending. Finally, there is no clear methodology for calibration of the impact of public R&D in relation to learning rates of which include both R&D and learning by doing effects.

5.4 Implementation in energy system models

Notwithstanding methodological and data concerns, additional questions arise when applying the TFLC endogenously in models.

Firstly, uncertainties with regard to R&D investments will become more pronounced when assuming future trends for the developments in R&D investments of the different scenarios. Here, the question arises on whether it will be better to use exogenous assumptions on future R&D investment levels, or to endogenise the calculation. The advantage of the latter is that consistent scenarios could be produced and data gaps would be filled. On the other hand, an endogenous calculation of corporate R&D – by e.g. assuming a constant R&D intensity multiplied with the sector's turnover; see section 5.2.2 above– implies a risk of exaggerating lock- in effects as with this method increased technology uptake would not only lead to learning by doing but also to increased corporate R&D funding levels. On balance, in the absence of a model simulating business R&D budgeting on the basis of risk and expectation, it may be preferable to leave R&D funding exogenously determined by considerations derived from the technology perspective analysis.

6. Conclusions and outlook

The workshop discussion has pointed out the strengths and weaknesses of applying the learning concept (with one or two factors) for a) explaining observed phenomena and b) using it in model projections.

In general, the One-Factor-Learning Concept is seen as a proven concept with sufficient data available. In recent years, better understanding of the mechanisms behind cost reductions through learning by doing (i.e. opening the 'black box' of learning curves) led to better replication of historic data. It turns out that technologies consist of parts that learn and others that do not learn; that there are cost-driving factors outside of learning by doing such as commodity prices; and that learning rates may need readjustment in the different phases of the innovation cycle. Moreover, a restriction of the learning concept to capital costs, only, may ignore improvements in technology performance; this could be captured by extending the learning approach to the levelised costs of energy and determine the overall cost behaviour by assessing the learning behaviour of each of its cost components.

With regard to the implementation of the learning curve in model tools – whether one or two factor – some questions remain. In particular, there is no clear-cut answer to how learning parameters are to be used in modelling exercises; the most important aspect when applying learning parameters is to highlight the uncertainties and the assumptions made. There is no answer to whether, or not, to use a technology-cluster approach; there is no answer to whether, or not, to use a floor price. Moreover, there are suggestions but no definite answer to whether, or not, the learning curve approach could be used for assessments when we experience (radical) changes in technology design (new types of PVs; new types of wind turbines etc.).

But despite these implementation challenges, the uncertainties in one-factor-learning curves do not prevent them from being useful for advising policy making and design. Modelling exercises are frequently used to assist decision makers, and the learning approach will not necessarily be more uncertain than any other modelling aspect. Even models themselves, being simplified representations of reality, may have an intrinsic uncertainty with regard to actual future developments.

Uncertainties, however, rise substantially when moving to the Two-Factor-Learning Curve, i.e. when trying to disentangle the effects of learning-by-doing from those of learning-by-searching. In particular, it is very questionable whether these factors can be considered isolated one from the other since they both form integral – and by far not the only – parts of the learning process. Experience showed that supporting RD&D without supporting deployment has proven to be a clearly suboptimal policy strategy. And equally, supporting deployment without supporting R&D seems to be suboptimal too.

Moreover, a quantitative relationship between research efforts and technology improvements will be difficult to obtain. Besides, the data basis for calibrating the TFLC is scarce especially for corporate R&D investments. But even if data was available, it remains questionable whether R&D investments are a suitable proxy for the knowledge

stock since they disregard e.g. the efficiency of research, network effects etc. The use of R&D intensities might be one suitable alternative here.

Despite the challenges arising around the application of the TFLC, policy makers will continue to demand quantification of the impacts of policy. These questions can range from providing a rule of thumb for the optimal balance (or band width) between R&D and deployment support, to the effect of R&D and deployment spending on the economy as a whole, to identifying gaps in the functioning of an innovation system and increasing the efficiency of policies by focusing on these gaps. Hence the need to research new and innovative methods and tools to provide policy makers with the best possible support is clear. The impact of R&D policy, with its inherently random nature, will continue to be a focus of policy maker's interests, and thus warrants further investigation.

Since the two-factor-learning curve is one of the few tools that try to quantitatively address these important topics, it may have its justification. However, considering the caveats with applying it for policy support, it becomes evident that more research is needed on it, probably proposing alternative formulations. But even an improved TFLC would not be able to satisfactorily answer the question on where is best to invest: research or deployment? The interdependence of both factors will categorically impede this.

One clear recommendation is that the assessment of increasing R&D efforts for low-carbon power technologies in EU will require complementary assessment studies applying alternate tools. Stochastic models or Monte-Carlo simulations have been suggested to analyse uncertainty, however this presumes we have more knowledge of the process of R&D. It could however be applied to the learning by doing side. Uncertainty could be addressed by giving ranges rather than one figure. E.g., in a recent paper (Nemet and Baker 2009) used expert elicitations and a bottom-up cost model to compare the effects of R&D and subsidies for a pre-commercial PV technology, organics. In this method, learning by doing is characterised using a traditional OFLC and R&D is characterised by aggregating expert judgements of technology outcomes under various R&D scenarios[5]. Other work has used a similar approach for a novel technology for which the reliability of cost estimates is even poorer (Nemet and Brandt, 2012). Multiple teams (e.g. Bosetti and Catenacci, 2012) are collecting elicitation data and they will soon be available to provide inputs to models of technology learning.

[5] http://www.nsf.gov/awardsearch/showAward.do?AwardNumber=0962100

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Annex 1 – Participants of the workshop "Learning Curves for Policy Support, held on 8th March 2012 in Amsterdam

Name	**Affiliation**
Giovanni De Santi	European Commission, JRC, IET Petten
Paul Dowling	European Commission, JRC, IPTS Seville
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Clas-Otto Wene	Wenergy AB
Tobias Wiesenthal	European Commission, JRC, IPTS Seville
Remko Ybema	ECN
Bob van der Zwaan	ECN

Annex 2 – Workshop programme

Venue: Trippenhuis - Royal Netherlands Academy of Arts and Sciences, Kloveniersburgwal 29, Amsterdam/ Netherlands – Meeting Room "Oude Vergaderzaal
Date: 8th March 2012

Time	Topic	Speaker
09h00-09h30	Welcome. Introduction	Directors of JRC-IET/ ECN: Giovanni de Santi/ Robert Kleiburg
09h30-10h00	Objectives of the workshop	Stathis Peteves (JRC-IET)
10h00-10h30	Learning rates (two-factor, multi-component): data issues, uncertainties, complementarities	Bob van der Zwaan (ECN)
10h30-10h50	Methodological issues on the Two-Factor-Learning	Clas-Otto Wene (Consultant)
10h50-11h00	Coffee break	
11h00-11h30	R&D Investments: data issues; uncertainties	Chihiro Watanabe (Tokyo Institute of Technology) – to be confirmed
11h30-12h15	SET-Plan quantitative impact assessment	Tobias Wiesenthal (JRC-IPTS)
12h15-13h30	Lunch	
13h30-15h30	Discussion, based on the written contributions received and the mornings presentations. Open questions: • The concept of TFLC (linkage knowledge stock - technology costs) • Uncertainties on parameters values • Uncertainties on R&D values • Alternative approaches to TFLC: floor costs; process simulation	Moderator: Peter Russ (JRC-IPTS)
15h30-15h45	Coffee break	
15h45-16h30	Wrap-up of key recommendations from Discussion, possible way forward	Peter Russ (JRC-IPTS) + direct expert feedback
16h30-17h00	Concluding remarks	Stathis Peteves (JRC-IET)

Annex 3 – Background note for the workshop

Objective

The expert workshop 'Learning Curves for Policy Support' aims to assess challenges in the application of the two-factor-learning curve, or alternative solutions in supporting policy decision making, and to provide options for improvement. The outcome of the workshop will be precise proposals on how to move forward with the quantitative impact assessment of the European Strategic Energy Technology Plan.

Context

Innovation is key for achieving the European energy and climate objectives. To this end, in February 2008 the European Union adopted a European Strategic Energy Technology Plan (SET-Plan)[6], which supports Research and Development and the market uptake of low-carbon energy technologies.
Raising R&D investments from both public and private funders is a cornerstone of the SET-Plan. The research investment gap has been analysed at the basis of individual technologies in a 2009 EU Communication[7], building on expert estimations. There is now a need to complement this bottom-up approach with a more systemic analysis of the impact of accelerated research efforts into multiple low-carbon technologies on the energy sector as a total.

A first attempt to quantify the impacts of R&D investment levels that are in line with the SET-Plan (but with similar efforts also pursued at global level) has been undertaken within the SET-Plan Information System[8][9]. It applies a methodology using the concept of Two-Factor-Learning, which quantitatively links trends in technology costs to both accumulated R&D investments and production volumes. The impact of the latter on the energy sector is then simulated in a consistent manner with the POLES global energy model. On this basis, two scenarios that both fulfil the EU's 2020 energy and climate objectives and differ only in their R&D investment levels have been compared. The results of this work indicate that the reduced technology costs induced by additional R&D investments allow support policies for renewables and carbon values to be lowered, and the cumulative (discounted) benefit of the accelerated research efforts are positive in the long term.

At the same time, this work points out a number of challenges on both the methodology and the underlying data, which significantly influence the results. In order to further develop this line of assessment in support of the SET-Plan, the present workshop will address these challenges in a structured manner, and come up with conclusions on how to move forward. Whilst acknowledging the importance of discussing methodological issues and data limitations, in order to continue to advance this line of research the workshop organisers (JRC/ENC) are looking for concrete and pragmatic solutions to the below issues.

Key topics addressed in the workshop

Four main areas of discussion have been identified, which are further explained below. These questions can be considered as a starting point for discussion between the experts. The discussion will focus on concrete solutions on how to address these challenges in order to provide the workshop with new ideas and solutions for future work.

1) Is the concept of the Two-Factor-Learning-Curve, i.e. the linkage of the knowledge stock to technology costs, a suitable approach?

- How to deal with the non-linear relationship between research inputs and outputs?
- Can the knowledge stock correctly be approximated by the R&D investment of the related technology (or sector), including some delay and depreciation rates? What about

[6] European Commission, Communication 'A European Strategic Energy Technology Plan (SET-PLAN) - Towards a low carbon future', COM(2007)723 final.

[7] European Commission, Communication 'Investing in the Development of Low Carbon Technologies', COM(2009)519 final.

[8] http://setis.ec.europa.eu/newsroom-items-folder/announcement-new-jrc-report-2018quantitative-assessment-of-the-impact-of-the-strategic-energy-technology-plan-on-the-european-power-sector2019

[9] T. Wiesenthal, A. Mercier, B. Schade, H. Petric, L., Szabo, Quantitative Assessment of the Impact of the Strategic Energy Technology Plan on the European Power Sector, JRC Report EUR24566, 2010.

- knowledge spillovers from other sectors and/or technologies and/or between military and civil applications?
- other crucial elements in the innovation chain besides R&D investments?

- Does it make sense to model learning regionally, or will it necessarily be at a global level (which would affect data problems, see point 3).

Practical ideas:

- Can one overcome discontinuities in R&D by expanding the concept of learning from a single technology to an entire sector that encompasses many individual technologies with distinct research successes, therefore 'smoothening' discontinuities?
- Can we expand the knowledge stock to also include demonstration investments, i.e. RD&D? At the same time, this may increase the problem of lack of data.

2) Do uncertainties in parameters (i.e. learning rates) impede a meaningful result?

- The learning rates can differ significantly for the same data sets across various approaches[10];
- Learning by doing and learning by researching effects are linked. They act as a virtuous self-reinforcing cycle[11];
- Taking into account the problem of separating economies of scale from learning, of internal feedback between various ways of learning and technological and national spill-over effects, there is a risk that learning rates are overestimated.
- Additional uncertainties arise when applying this concept to assess future trends in technology costs:
  - learning rates may decrease at a higher maturity of the technology[12],
  - the total decrease in costs is limited
  - reinforcing effects are over-estimated.

Practical ideas:

- Uncertainties in parameters might be addressed by sensitivity runs, or a full sensitivity analysis involving e.g. Monte Carlo Simulation and subsequent comparison of the robustness of preferring one policy against another[13].
- One may assume learning rates to decrease over time. Another way of addressing this in a model may be the introduction of floor costs.

3) Do uncertainties in data (e.g. R&D investments) impede a meaningful result?

- There is no single database that contains industrial and public R&D investments at the level of detail of individual technologies.
- In particular for corporate R&D investments, a number of assumptions need to be made.
- This becomes even more pronounced when assuming future trends for the developments in R&D investments.
- Moreover, the approximation of the knowledge stock by the cumulative R&D investments disregards improvements in the efficiency that research is being performed.

Practical ideas:

- Corporate R&D investments could be linked to the turnover of a sector (through the R&D intensity). The turnover could be approximated in a model by the unit cost times the installed capacity; hence, corporate R&D investments could be endogenised.
- Probably a large number of scenarios need to be analysed with the aim to identify trends.

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[10] P. Söderholm, T. Sundqvist, Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies, Renewable energy; U.K. Rout, M. Blesl, U. Fahl, U. Remme, A. Voß, Uncertainty in the learning rates of energy technologies: An experiment in a global multi-regional energy system model, Energy Policy 37 (2009), 4927-4942.

[11] C. Watanabe, Industrial dynamism and the creation of a virtuous cycle between R&D, market growth and price reduction—the case of photovoltaic power generation (PV) development in Japan. In: C.O. Wene, A. Voss, T. Fried (Eds.), Experience Curves for Policy Making: The Case of Energy Technologies, Proceedings IEA Workshop 10–11 May 1999, Stuttgart, Germany.

[12] U. Claeson, Experience curves for policy making: the case of energy technologies, In: C.O. Wene, A. Voss, T. Fried (Eds.), Experience Curves for Policy Making: The Case of Energy Technologies, Proceedings IEA Workshop 10–11 May 1999, Stuttgart, Germany.

[13] B. Schade, T. Wiesenthal: Biofuels: A model based assessment under uncertainty applying the Monte Carlo method. Journal of Policy Modeling, Vol. 33, No. 1, 2011, pp. 92-126.

4) How best to include learning in modelling?

- How to account for the fact that there is a limit to learning?
- Shall learning be modelled for a technology, a sector or parts of a technology?

Practical ideas:

- A limit to learning could be modelled through the use of floor costs. Hence, the learning would basically describe the development over time to bring down costs, but not the ultimate level of cost reductions. Yet, also floor costs are associated with uncertainties.
- If learning applies more to a component of a single technology rather than to a sector, maybe the use of process simulation models is more appropriate.

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Abstract

The European Commission's Joint Research Centre and the Energy Research Centre of the Netherlands (ECN) organised an expert workshop on 'Learning Curves for Policy Support' in Amsterdam on 8 March 2012. It aimed to assess the challenges in the application of the two-factor learning curve, or alternative solutions in supporting policy decision making in the framework of the European Strategic Energy Technology Plan, and explored options for improvement. The workshop gathered distinguished experts in the field of scientific research on learning curves and policy researchers from the European Commission and ECN to assess the challenges in the application of the two-factor-learning curve, or alternative solutions in supporting policy decision making, and to provide options for improvement.

This paper forms the summary of outcomes from the workshop. Due to the very different nature of the One-Factor-Learning concept and the Two-Factor-Learning concept, these are discussed in separate parts. In each of these parts the context and the methodology are introduced, methodological and data challenges are described and the problems associated with the application of the concept in models is discussed.

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