

Energy Technology Learning - Key to Transform into a Low - Carbon Society

Clas-Otto Wene
Wenergy AB
Sweden

1. Introduction

Experience enhances capacity for effective action. Exploiting markets to provide experience on new technologies is the key to a low-carbon society.

As market actors in the whole chain from technology producer to technology operator and user accumulate experience, both cost and technical performance of the technology improves. This process is referred to as *technology learning* (IEA, 2000). *Learning curves* (Wright, 1936) and *experience curves* (BCG, 1968; Abell and Hammond, 1979) measure the results of the process.¹

Understanding the process of technology learning is of fundamental importance for a cost-efficient technology-led transformation into a low-carbon society. The implications of the process for energy technology policy were discussed at a workshop convened by the International Energy Agency in 1999. The IEA Workshop recommended that experience and learning curves “are used to analyse the cost and benefits of programmes to promote environment friendly technologies” and “explicitly considered in exploring scenarios to reduce CO₂ emissions and calculating the cost of reaching emissions targets” (IEA, 2000, Appendix B). The IEA Committee on Energy Research and Technology (CERT) supported the findings of the Workshop and initiated an international collaboration (IEA, 2000, Appendix C). Technology learning is a key process in the global scenario analysis within the IEA Energy Technology Perspectives bi-annual publications (IEA, 2006; 2008; 2010a). More importantly, the IEA work together with other recent high-level policy documents embrace the insights from experience and learning curves into the crucial role of government deployment programmes to make low-carbon energy technologies cost-efficient (Stern, 2006; EESC, 2009).

The IEA 1999 Workshop and subsequent work pointed to two major areas where technology learning should inform and guide energy technology policy: exploring and calculating cost for CO₂-reduction scenarios and designing efficient deployment programmes.

Kahouli-Brahmi (2008) provides an overview of global scale models incorporating technology learning to investigate CO₂-reduction scenarios. The first investigations by

¹ The paper follows BCG (1968) in distinguishing between learning and experience curves. The experience curve relates the performance of the learning system to total input, which is usually expressed as total costs. A learning curve relates the performance of the learning system to one of the inputs, e.g., labour, raw materials, energy, or to a subset of inputs.

Messner (1997) and Mattsson and Wene (1997) using technology-rich, bottom-up models show that technology learning drastically reduces the cost to achieve CO₂-targets compared to earlier studies. This is an expected outcome because technology learning will reduce the cost of new low-carbon technologies following their implementation in the energy system; the higher the rate of technology deployment, the higher the rate of technology cost reductions. The energy system thus creates its own cost-efficient technologies. However, the results also identified three issues for legitimacy and design of deployment programmes. The issues can be labelled as alternative technology paths, high up-front costs, and global learning vs. local deployment (IEA, 2000; Wene, 2008a).

The fact that future costs of technology depend on earlier deployment in the energy system presents the prospect of equally effective systems but relying on very different, alternative technology paths. Experiment with a global, optimising model shows low and high carbon energy systems with the *same* present cost. The costs are calculated without imposing any form of external carbon costs, e.g., in the form of tax or trading schemes (Mattsson and Wene, 1997; IEA, 2000, pp. 84-91). Alternative systems have also been studied by Rao et al. (2006). The low-carbon technologies thus have a large potential for becoming the future cost-efficient choice in the energy system. However, the annual cost profiles for the low and high carbon cases are quite different. The new technologies required for the low-carbon case requires considerable up-front investments to initiate technology learning and keep the technologies riding down the experience curve. The up-front costs function as learning investments that are paid back as the technology becomes cheaper. But in the short range they appear as a large cost barrier to climb over in order to reach and realize the low-carbon system. Without special measures to support such climbing, the energy system risks lock-in to the high-carbon technologies. The alternative technology paths and the high up-front costs for the low-carbon alternative therefore provide strong legitimacy for proactive government deployment programmes to aid development of desired energy technologies.

IEA (2003) provides an overview of deployment programmes illustrated by 22 national case studies. Cost barriers for technologies already close to cost-efficiency are a few billion US dollars and can be overcome with the help of general low-carbon incentives, e.g., carbon trading schemes. However, overcoming the cost barriers of many promising large-potential technologies, such as photovoltaic electricity and deep water off-shore wind power, may require up to several hundred billion US dollars. Such technologies need targeted deployment programmes, for instance feed-in tariffs, to initiate and maintain learning towards cost-efficiency. The large investments in learning must be shared among the market actors but their magnitude also underscores the importance of precise predictions of the learning effect. Fairly small uncertainties in experience and learning curves proliferate to large uncertainties in cost estimates.

Once an emerging new technology has reached the world market the learning is governed by global deployment, so the sharing of learning investments eventually becomes a global issue. Development of wind power illustrates the progress from national to global learning. The first measurement of the experience curve for wind turbines was made by Neij (1999) for the Danish industry for the period 1982-1997. German markets did not take off until 1992 when the government started the 100 MW Wind deployment programme which later become the 250 MW Wind (IEA 2000, pp. 52-64). Durstewitz and Hoppe-Kilpper (1999) measured the experience curve for Germany for the period 1990-1998. Comparing data from different national programmes, Junginger et al (2005) could establish a global experience curve for wind power plants.

The global learning challenges both national policies and cohesion of international community because the deployment required for the learning is based on local decisions. A technology-led transformation to a low-carbon system therefore requires concerted action on deployment programmes among governments to provide learning. National governments may hesitate to align themselves to an international scheme and prefer to wait until actions by other countries have provided cost-efficient low-carbon technologies. If too many countries take a wait-and-see stance the cost-efficient technologies will never materialize. IEA (2000, pp. 64-74) analyses the Japanese "Roof-top" programme to support learning for PV-systems and concludes that reaching the cost target requires considerable deployment outside Japan. Martinsen (2010, 2011) has studied global learning vs. local deployment from the perspective of a small, open economy. His results indicate that there may be considerable advantages for such an economy to align itself to international efforts on deployment.

Technology learning also challenges the scientific community to provide a better understanding of the technology learning phenomenon. Using experience and learning curves to argue for legitimacy and efficiency of aligned government deployment programmes requires that these curves can be confidently extrapolated into the future. The Stern (2006) report observes that "data shows technologies starting from different points and achieving very different learning rates". The observation is confirmed by compilations of experience and learning curves (Dutton and Thomas, 1984; McDonald and Schratzenholzer, 2001; Weiss et al., 2010). Nemet (2009) interprets the observed spread of learning rates for the same technology in different time-segments as an indication of the uncertainty in extrapolating the curve. The uncertainties in key parameters such as buy-down costs or year of break-even then become too large to permit quantitative policy conclusions. In their report to the 2006 G8 meeting of Head of States, the International Energy Agency finds:

"Technology learning is the key phenomenon that will determine the future cost of renewable power generation technologies. Unfortunately, the present state-of-the-art does not allow reliable extrapolations" (IEA, 2006, p. 231).

Although there is consensus on the importance of technology learning to achieve a low-carbon energy system, there are therefore considerable doubts about quantitative estimates of costs and dynamics from experience and learning curves. The uncertainty about the extrapolated curve hampers the design of efficient deployment programmes and thereby hinders the full exploitation of technology learning to transform the system. Obviously, the state-of-the-art of exploiting technology learning must be improved.

The purpose of this paper is to discuss the two challenges from technology learning: providing confidence in extrapolating experience and learning curves and achieving global learning based on local deployment.

The ambition of the paper in meeting the two challenges are quite different, however. It is argued that the uncertainty in extrapolation can be effectively reduced through a better theoretical understanding of technology learning. Recent advances in a cybernetic approach to understand the phenomenon indicate that the observed dispersion of learning rates are due to the learning system adapting an internally well-defined learning mode to external perturbations (Wene, 2007, 2008a, 2008b, 2010). The existence of these internal modes provides stability to the extrapolation. The discussion of global learning vs. local deployment is limited to an illustrative example where the new theoretical understanding is

applied to the global decarbonisation curve. It is based on the approach proposed in IEA (2000, pp. 75-84) and using data and scenarios from the recent World Energy Outlook (IEA, 2010b).

The following section discusses the phenomenon of technology learning both under normal market conditions and during radical technological change. Section 3 presents the theory and applies it to explain observed distributions of learning rates. The global decarbonisation curve is discussed in section 4.

2. Technology learning: Phenomenology

2.1 Continuous improvement in equilibrium markets

Figure 1 shows the experience curve for photovoltaic (PV) power modules. Since 1976, prices have been reduced from over 60 USD(2001)/W_p to around 3 USD(2001)/W_p today. The straight line is the experience curve fitted to the time series. Both scales are logarithmic, so the experience curve can be written as

$$\text{Price}(t) = C_0 * X(t)^{-E} \tag{1}$$

Price at time t is equal to a constant, C₀, times the cumulative sales X(t) at time t raised to the power of -E. E is a constant and will be referred to as the experience parameter. The value of this constant is to be explained by the theory.

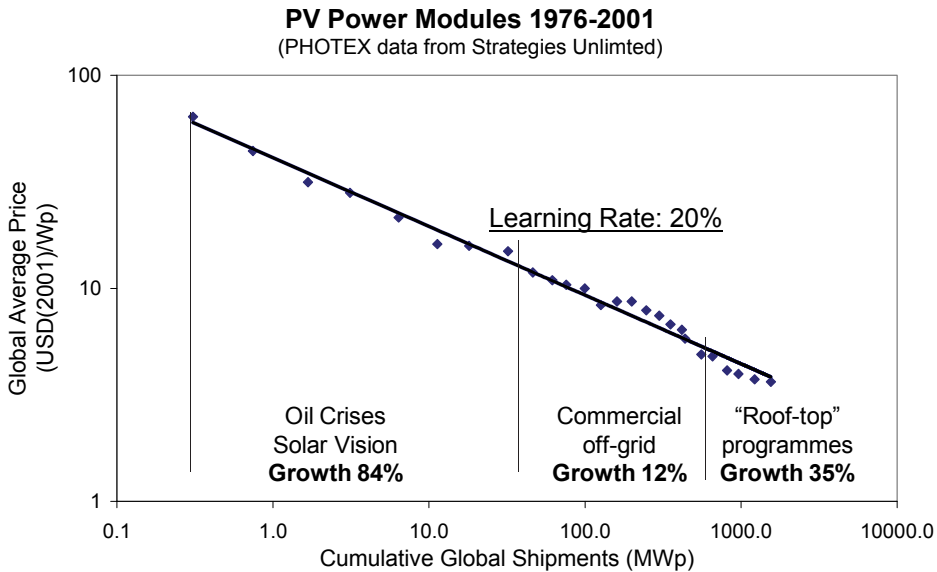


Fig. 1. Experience curve and growth in global sales for photovoltaic modules (data for experience curve from Schaeffer et al., 2004; Wene, 2008b).

The literature uses not E but learning rate, LR, or progress ratio, PR, to characterize the steepness of the curve. The learning rate is the relative reduction in price for each doubling of cumulative sales. The relation between E, LR and PR is given by

$$PR = 1 - LR = 2^{-E} \quad (2)$$

The fit of the experience curve to the PV time series is good with a $R^2 = 0.9868$ indicating stable conditions for the learning system. The learning rate for PV modules is constant at 20% over three decades and almost four orders of magnitude in cumulative global sales. The stability of learning is quite impressive, considering the great swings in market growth caused by instable government deployment programmes. One conclusion is that learning rate is independent of growth rate. However, the example in Figure 1 raises the issue of using price or cost to measure the performance of the technology learning system.

The learning effect in Figure 1 is measured by price, which is set by the actors in the market. Competitive markets are necessary to foster learning, but the observed learning is the result of internal operations within the learning system, which in Figure 1 is the PV-module production system. Technology learning should be measured by cost rather than price. The theory will use cost as the variable to be explained. However, reliable cost data are difficult to obtain and the experience and learning curve literature usually measures the learning effect by price series. It is therefore crucial to clarify the relationship between cost and price. The analysis in BCG (1968) (see also IEA/OECD, 2000, pp.35-40) shows that the ratio between price and cost remains constant in equilibrium markets, i.e. performance measured by price and cost have the same learning rates in this case. However, market disequilibrium may initiate a price-cost cycle, which shows up as systematic deviations from the experience curve measured by price. The launching of a new product may cause such disequilibrium.

2.2 Radical innovation

Freeman and Perez (1988) distinguish between four types of technological change: incremental and radical innovations and changing technological system and technological paradigm. We look at individual technologies and are interested in the two first types for characterising processes and operations in the learning system. The continuous logarithmic form of the experience curve for PV power modules suggests that the learning system moves ahead using incremental innovations. However, stepwise changes in curves for oil exploration as in figure 2 indicate major technological changes in this area due to radical innovations.

Price-cost cycles may also lead to stepwise changes in the curves (BCG, 1968) so price curves are poor indicators for radical change. The learning curve for wildcats² (Wene, 2005) in Figure 2 is based on physical measurements and thus avoids price-cost ambiguity. It is, however, a learning curve³ and does not relate performance to total inputs so it ignores effects due to changing oil resources. The following analysis assumes depletion but no stepwise changes in these resources. Between 1947 and 1968, the learning curve remains practically horizontal representing the tail end of a curve that started many decades before. An experience curve should still show improvements, the flat learning curve indicates that any such improvement is masked by depleting oil resources. The interesting features of this curve are the steep improvements in performance after 1968 and after 1989.

² A wildcat is an exploratory borehole in an area that has not before produced any commercial amount of oil.

³ See footnote 1. The output is successful wildcats and the performance of the system is related to total wildcats, that is performance = total wildcats/successful wildcats.

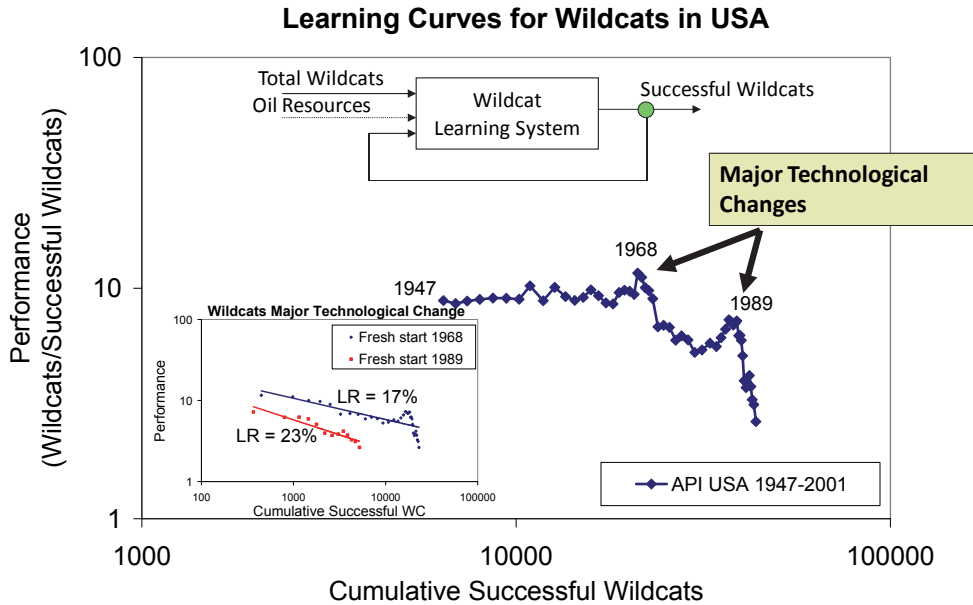


Fig. 2. Learning curve for wildcats in the USA (Wene, 2005, 2008a)

The stepwise improvement in wildcat performance is directly correlated to major technological changes in oil exploration (Wene, 2005). Computer technologies applied to seismic imaging explains major parts of these improvements. The use of 3D seismic technology for new wildcats took off around 1990 and the area covered by this imaging technology grew from five thousand to over one million square kilometres between 1991 and 2000.

The correlation to observed major changes in exploration technology permits the conclusion that the stepwise changes in the wildcat learning curve are the signature of radical innovations. The question is how radical innovations should be included in the technology learning methodology. Fitting learning curves to the steep parts of the curve result in ridiculously high learning rates. The inset diagram shows that resetting the cumulative output of the learning system to zero in 1968 and 1989, respectively, provides fairly good fits to data. It is interesting to note that the learning rates after reset are close to the 20% rate found for PV power modules. The theory for technology learning presented in the next section supports this representation of the effect of radical innovations (Wene, 2007, 2010).

Figure 3 shows the experience curve analysis of cost data for oil exploration in the period 1985-1999. Using historical cumulative findings from 1968 provide a learning rate of 76%, which obviously has not prognostic value. Resetting cumulative findings at 1989 provides LR = 28% which is still larger than for wildcats but could reflect the uncertainty in valuing oil resources. We will return to radical innovations and their representation when discussing the decarbonisation curve in section 4.

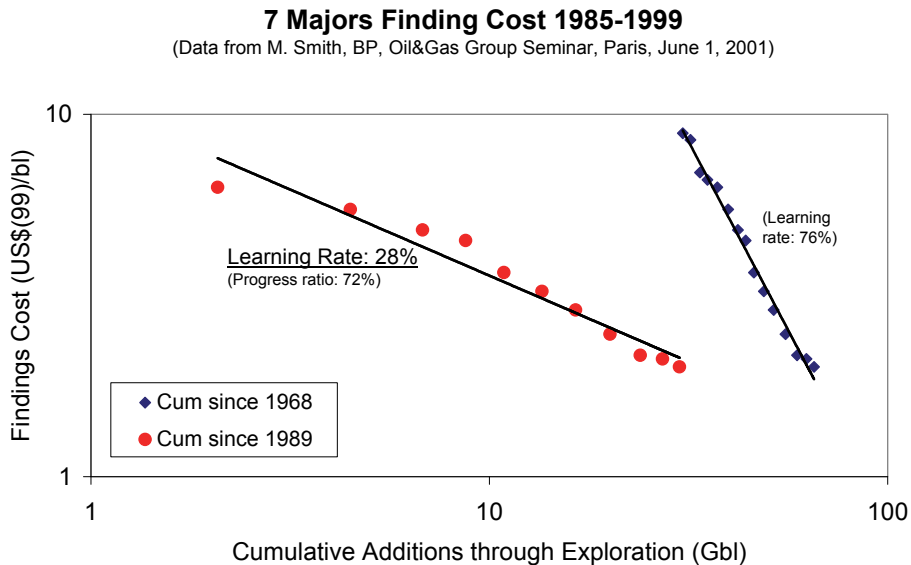


Fig. 3. Experience curve analysis of oil exploration (Wene, 2005).

3. Technology learning: Theory

3.1 The cybernetic approach

Several mechanisms have been proposed to explain technology learning and the observed relationships (Abell and Hammond, 1979; Arthur, 1988; Argote and Epple, 1990; Adler and Clark, 1991; Nemet, 2006), but generally they fail to reconstruct the shape of the curves or explain the observed learning rates. Ferioli and Zwaan (2009) using a top-down approach reproduce the shape, provided market growth is exponential and that actually realised incremental improvements diffuses out from a pool of potential improvements. All these explanations understand learning as the result of an open system reacting to demands and opportunities in the environment thus focusing on the role of environmental interactions in explaining the phenomenon. The operations of the learning system are assumed to be determined by features, events and processes (FEPs) in the system environment.

Contrary to earlier proposals, the cybernetic approach (Wene, 2007, 2008a, 2008b, 2010) considers technology learning as *inherent property* of the learning system. Experience and learning curves express the *eigenbehaviour* (Varela, 1979, 1984; von Förster, 1984, 1993) of an operationally closed system producing for a competitive market but acting autonomously based on its internal structure. The approach applies fundamental theoretical results for biological and social systems (von Förster, 1980; 2003, Varela, 1979, 1984; Luhmann, 2002).

The condition of operational closure means that the system forms and controls all its operations. The system is open to information and to material and energy flows; however, the network of internal operations closes on itself. The condition of operational closure has a very important consequence expressed in the closure theorem of cybernetics: *in every operationally closed system there arise Eigenbehaviours*. The task is to find the operational loops

that represent learning and define the operators whose fixed points provide the values for the eigenbehaviour. Wene (2007; 2008a) provided a hypothesis for the operational loops and defined two operators, C_{SRL} and C^+ , expressing system performance and the dependence of this performance on cumulative system output.

The following provides a brief review of the results from the theory. The purpose is to demonstrate the stability of technology learning and provide grounds for reliable extrapolations. Wene (2007, 2008a, 2010) provide a detailed presentation of the mathematical formalism including justification of operator loops and equations from studies of organisational learning (Kim 1993; Espejo et al, 1996).

The condition of operational closure makes it possible to postulate an internal state, Z , for the learning system. The fact that all operational loops are closed and that the system is the master of all its operations guarantees that such a postulate is meaningful. The operators act on the internal state and the results can be interpreted as, e.g., values of the experience parameter. The basic eigenvalue equation in the theory provides the results in the limit of repeated operations

$$\underline{Z}_\infty = \lim_{\tau \rightarrow \infty} \begin{pmatrix} C_{SRL} & W_{12} \\ W_{21} & C^+ \end{pmatrix}^\tau \begin{pmatrix} \Delta P_0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} i \\ 1 \end{pmatrix} \quad (3)$$

The 2/1 matrix is the original system state, Z_0 . Following Wene (2007) it is assumed to be the base vectors of the complex Argand plane. Equation 3 is derived under the assumption that equation 1 expresses the relation between performance and cumulative output from the learning system. τ is the amount of doublings since the system became operationally closed. In this case ΔP_0 is a constant and equal to the relative improvement in performance for each doubling of cumulative output⁴. W_{12} and W_{21} are operators representing operations in the learning system in order to manage external perturbations; in cybernetic language they represent the *plasticity* of the system.

The solution of equation 3 can be envisaged in two steps. The first step calculates the main learning modes, which represent the spectrum of stable eigenbehaviours of the system. The second step considers the systems adaptation to external FEPs. The FEPs can be negative or positive that is reducing or increasing learning. Examples of FEPs are regulations, results from public Research & Development (R&D), government stimulation of private industry R&D, changing consumer behaviour, spillover and crossover from other learning systems or technology fields.

Setting $W_{12} = W_{21} = 0$ in equation 3 provides the solution for the main learning modes discussed in detail in Wene (2007, 2008a). The experience parameters corresponding to the main learning modes are

$$E(n) = 1/[(2n + 1) \cdot \pi] \quad n = 0, 1, 2, 3, \dots \quad (4)$$

⁴ A more general formulation is that ΔP_0 is the relative improvement in performance between two logarithmically equidistant measures of cumulative output. However, we have chosen to set the numeric equal to doubling of cumulative output.

Following equation 2, the four first modes of learning are then

$$LR(0, 1, 2, 3) = 20\%, 7\%, 4\%, 3\%, \dots \quad (5)$$

The question of terminology should be brought up here. Wene (2010) somewhat loosely refers to all the main modes of learning as “unperturbed”. Strictly speaking, however, only the basic mode of $LR(0)=20\%$ can be unambiguously referred to as “unperturbed”, meaning that it represents the learning in a system exposed to no other external perturbations than those FEPs normally appearing in a competitive market in equilibrium. For the purpose here it is important however, that all the main modes are stable, meaning that if an external perturbation results in the system moving away from a main mode given by equations 4 and 5, the system will return to the eigenbehaviour representing the original main mode when the perturbation disappears. There are, however, under special circumstances exceptions to this rule of stability. These exceptions are discussed below. It is also possible that, under favourable circumstances, a learning system in a higher mode with $n>0$ could switch to the basic mode with $LR(0)=20\%$. Borrowing terminology from physics, learning modes with $n>0$ could be characterized as meta-stable. We will not here speculate over such a bonus for technology policy, but will in the following retain the characteristic “stable” for all main learning modes with the caveats given above.

The off-diagonal operators, W_{12} and W_{21} , show how the system adapts to external perturbations. Their effects on the system are quite different. W_{12} shifts the system away from the stable eigenvalues, while W_{21} directly affects the internal memory manifested in cumulative output. One could use cumulative output to define an eigentime for the system. W_{21} can reset this internal clock and in the same way as a radical innovation can reset cumulative output. In this paper we will only discuss the effects of W_{12} on the stable eigenvalues.

Let ΔP_0 provide a measure of the strength of the perturbation and W_{12} be parameterized as (Wene, 2010)

$$W_{12} = \alpha(\tau) \cdot \Delta P_0 \cdot C^+ \quad (6)$$

where $\alpha(\tau)$ is a negative or positive real number. For *negative* α -values the initial eigenvalues are modified by the perturbation and for a perturbation of fixed strength converge to provide an experience parameter

$$E_\infty(n, \alpha) = 1 / [(2n + 1) \cdot \pi - \alpha] \quad n = 0, 1, 2, 3, \dots \quad (7)$$

As expected, a negative perturbation will thus *reduce* the learning rate. When the perturbation disappears the system returns to its initial stable eigenbehaviour. The system may, however, adapt quite differently to a positive perturbation. Equation (6) continues to characterize the behaviour of the system immediately after the onset of a positive perturbation, leading as expected to an increased learning rate. However, if the positive perturbation remains the system will start to align itself to the perturbation. The result is a phase shift where the new experience parameters converges to

$$E_\infty(n, \alpha) = 1 / [(2n + 1) \cdot \pi + \alpha] \quad n = 0, 1, 2, 3, \dots \quad (8)$$

An external feature, event or process providing a free positive contribution to the system performance but remaining too long will eventually result in a reduction of the learning

rate. At first this result seems strange and counter-intuitive, but by reflection plausible. An interpretation is that the system gets accustomed to the free contribution to its learning and start losing its own ability to learn. The time until the onset of the phase shift depends both on the strength of the positive perturbation and on the age of the learning system. A system that has gone through many doublings of the cumulative output is more resilient but a younger system will rapidly degrade its own learning ability if exposed to free positive learning contributions. The stronger the positive perturbation is the faster it will produce a phase shift. The strength dependence effectively puts upper limits on learning rates. The phase shift has consequences for the possibility to increase learning rates by public R&D.

The analysis so far has supported our original conjecture about the stability in extrapolation of learning rates with the caveat that insistent positive perturbations may induce a phase shift. The risk of a phase shift is however, larger for challengers that just enter the market than for technology that already has made several doublings of cumulative output. The next step is to search empirical support for the theory. The following section finds such support in compilations of learning rates.

3.2 Empirical support from compilations of learning rates

In order to calculate distributions of learning rates, LR, or experience parameters, E, we introduce a simple probabilistic model for the distribution of perturbations. In the model, all perturbations are additive, and negative and positive perturbations are Poisson distributed. For the simple calculations presented here we further assume that perturbations start at the beginning of each measuring period and continue throughout the period. A detailed presentation of the model is given by Wene (2010). The probabilistic model can be considerably improved by considering, e.g., distribution of strength and duration of perturbations; however, it captures the essential aspects of the distribution.

Figures 4 -6 show fits of the probabilistic model to three published distributions of learning rates. The Dutton and Thomas (1984) distribution is based on cost time series for a broad spectrum of technologies in individual enterprises. Weiss et al. (2010) provide the distribution of learning rates for energy supply and energy demand technologies based on market prices. The distributions in figures 5 and 6 show the dispersion of learning among industries rather than among enterprises. For the comparison the learning rates have been recalculated to experience parameters using equation (2).

The experience parameters and learning rates for the stable learning modes are uniquely given by equations (4) and (5). They are thus independent of any fitting procedures. However, three parameters in the probabilistic model are fitted to the *dispersion* around the stable modes. These parameters are the intensities λ_{pos} , λ_{neg} of positive and negative perturbations, respectively, and the strength S_{FEP} of each perturbation. S_{FEP} is a constant meaning that all perturbations are assumed to have the same strength. The fit only considers the two first stable learning modes and the relative strength of these modes is also a fitted parameter. The fifth parameter is the cut-off parameter indicating the limiting value for positive perturbations; all positive perturbations larger than this value is assumed to lead to a phase shift. This sharp cut-off value simplifies the theoretical results in the previous section, which showed a much smoother cut-off, but is accurate enough for the calculations here. The cut-off can be varied within a narrow band of values constrained by theory.

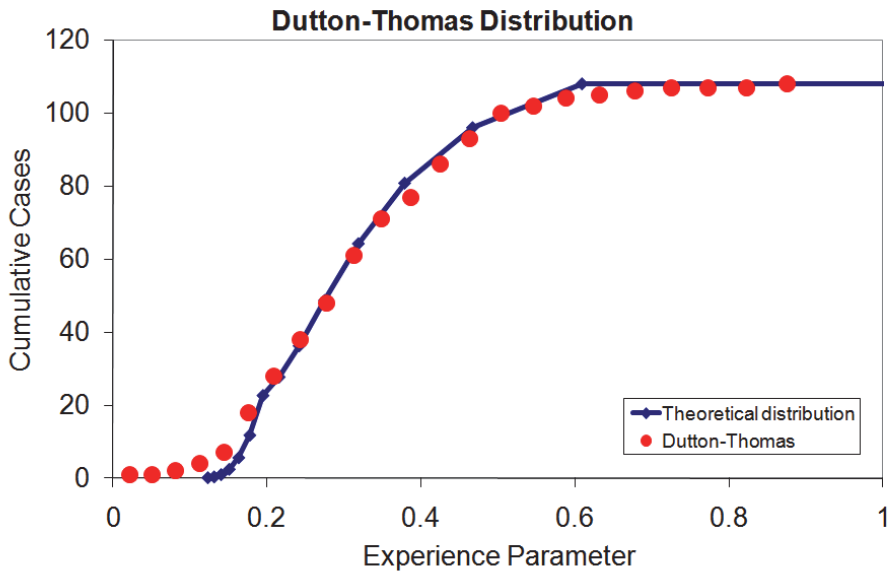


Fig. 4. Probabilistic model fitted to Dutton and Thomas (1984) distribution.

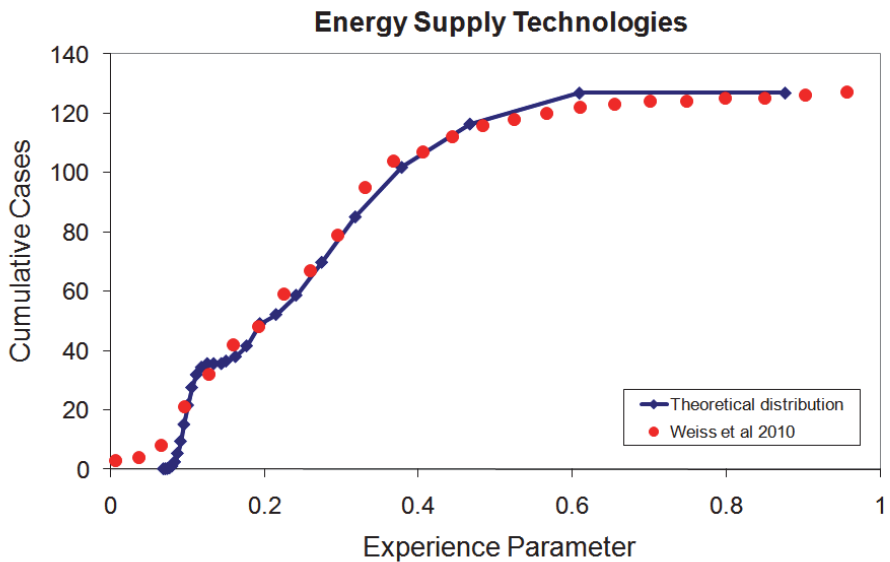


Fig. 5. Probabilistic model fitted to Weiss et al. (2010) distribution of learning rates for energy supply technologies

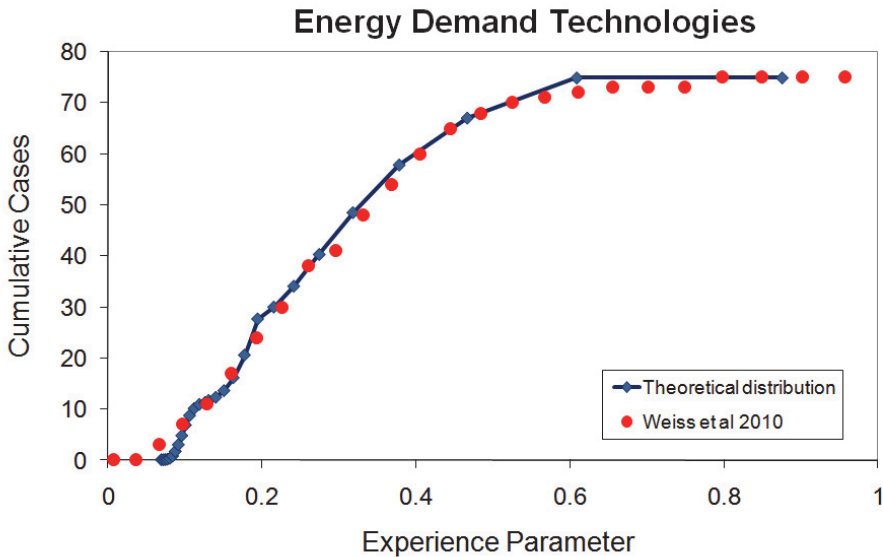


Fig. 6. Probabilistic model fitted to Weiss et al. (2010) distribution of learning rates for energy demand technologies

Table 1. shows results of fit with the probabilistic model and permit some initial observations.

Distribution	Cases	L0 strength	L1 strength	λ_{pos}	λ_{neg}	SFEP	Cut-off
Dutton & Thomas	108	1.0	0	4	3	0.5	2
Energy Supply	127	0.72	0.28	3	2	0.5	2
Energy Demand	75	0.85	0.15	4.5	3	0.5	2

Table 1. Parameters used in the probabilistic model to fit distributions. The same parameters are used for the L0 and L1 learning modes

The first observation is that the theory presented in the previous section explains the observed dispersion of learning rates or experience parameters among technologies. The probabilistic model based on the extended cybernetic theory for technology learning provides an equally good fit to all three distributions. This supports the claim that distributions are the results of learning systems adapting unique and common learning modes to external perturbations. However, the values of the fitted parameters point to differences between the distributions. These differences must be explained within the theory in order to make confident extrapolations of experience and learning curves. Wene (2008b, 2010) discusses causes for the differences and his arguments are briefly recapitulated here together with some new observations.

The three distributions are fitted assuming the same strength, S_{FEP} , and Table I shows that the relation between positive and negative perturbations are about the same for all three sets

of learning systems and technologies. However, the intensities λ_{pos} , λ_{neg} are 20-30% lower for the energy supply technologies compared to Dutton and Thomas distribution, while they are almost the same as in Dutton-Thomas for the energy demand technologies. The difference for the supply technologies is expected, but the results for demand technologies will require further studies.

Moving from a set of individual enterprises to a set of industries should reduce the dispersion – provided all firms within an industry compete on the same market with the same technology. This follows from the central limit theorem in mathematical statistics (Gut, 1995, pp. 173-177). Weiss et al (2010) distribution for energy supply technologies represents industrial averages over actions of several firms, while Dutton and Thomas (1984) shows the variance for a representative set of individual firms. Applying the central limit theorem would indicate that energy supply distribution represent averages over 2-3 firms, however, more detailed probabilistic models are necessary to verify this.

The question remains why industries producing energy demand technologies do not show the same reduction in dispersion as industries producing supply technologies. A hypothesis is that there is a much bigger dispersion among firms and marketed products within an industry producing demand than one producing supply technologies. E.g., a washing machine sold to an urban apartment is quite different from one sold to a hospital or hotel. The condition of a unique technology on a unique market is therefore not fulfilled and the central limit theorem cannot be directly applied. However, this hypothesis has to be investigated further.

A major difference regards the occurrence of higher order learning modes. Dutton and Thomas (1984) distribution shows none or negligible influence from higher order learning modes. However, the analysis of the two distributions of Weiss et al. (2010) verifies the observation made for the earlier McDonald and Schrattenholzer (2000) distribution for energy technologies (Wene, 2008b). The dispersion of learning rates for energy supply and demand technologies cannot be explained without higher order learning. The application of the probabilistic model indicates that 28% of the learning systems producing energy supply technologies and 15% of those producing demand technologies are in higher learning modes. The theoretical curves in figures 5 and 6 only show the effect of the first higher learning mode ($LR(1) = 7\%$) using the same parameters in the probabilistic model as for the zero mode. Including still higher order learning may improve the fit.

Wene (2008b, 2010) points to three possible causes for the appearance of higher order learning: system boundaries, environmental and safety regulations, and – more speculatively – government R&D. More important for this paper is to ask if switches between learning modes can take place in the future, upsetting the stability of extrapolations. The preliminary answer is that such switches cannot be ruled out but the risk of switching to higher learning modes or the opportunity of reaching a lower one will depend very much on policy design, i.e. decisions taken by policy makers. To aid such decisions requires more studies of the causes for the appearance of higher learning modes.

Another issue for the theory is the occurrence of very high learning rates in all the three distributions in figures 4-6. The rates are larger than the expected limit set by the phase switch. One explanation for the high learning rates is extreme events in input markets, e.g., labour, capital or raw material markets. Such events may decouple system dynamics from the learning loops and make it appear as trivial input-output machine (von Förster, 1984, 1993) responding to changes in the input markets.

So far, the theory is used to investigate and compare learning for individual technologies. In the following section it is used to characterize scenarios and study the collective effects of technology deployment on the global scale.

4. Decarbonisation as technology learning

Most global energy studies use energy models that build up scenarios from analysis of technology investments and energy flows in regions and major countries. They capture albeit with varying detail the effects of local technology deployment. The question is what type of learning this provides on a global scale. The focus is not on individual technologies but how learning is manifested in the total performance of the global energy system. Following a suggestion in IEA (2000, pp. 75-78) the global decarbonisation learning curve is chosen as a measure of system performance. Carbon in the form of non-renewable biomass, coal, oil and natural gas is one input to the global energy system. The useful physical energy flows drives the economic system, which also learns to use these flows more and more efficiently. Including demand technologies and energy efficiency measures into the system, global GDP emerges as a useful indicator for the output from the global energy system. The decarbonisation learning curve is the carbon intensity of global GDP as function of cumulative global GDP.

International Institute for Applied Systems Analysis (IIASA) in Austria pioneered long-range decarbonisation studies in the 1990s. Nakicenovic (1996) reports from a study of the US economy over the 140-year period from 1850 to 1990. The results show a simple power relation as in equation (1) between carbon intensity and cumulative carbon input. The learning curve concept states that performance depends on cumulative output. Converting to cumulative US GDP provides a learning rate for decarbonisation of 18% that is quite close to the 20% provided by theory.

It may seem surprising that decarbonisation was an historical trend long before climate change became an issue. However, increased energy efficiency driven by technology development and fuel switching to more easily managed fossil fuels, which just happened to have less carbon, explain most results. Macroeconomic modelling provides some quantitative insights. Economic modellers have used the concept of Autonomous Energy Efficiency Improvements, AEEI (Manne and Richels, 1992) to capture effects of technology development. AEEIs equal 0.5% and 1% are frequently assumed, which corresponds to yearly, not price-induced improvement in energy intensity of the economy of 0.5% and 1%, respectively. At 3% economic growth and everything else equal, such values for AEEI corresponds to learning rates of 12% and 21 %, respectively. Economic and learning curve analysis seem to concur on the historic trend of decarbonisation. However, this trend is by far not enough to ensure stabilisation and reduction in CO₂ emissions. The question is how to improve on the historic trend. To understand the implications of this question we turn to the scenario makers.

For the decarbonisation analysis we choose the scenarios in the well-known IEA World Energy Outlook (IEA, 2010b). There are several reasons for this choice. WEO scenarios build on considerable amounts of world statistics assembled at IEA since its foundation in the 1970s. WEO can rely on policy analysts and energy consultants within all IEA governments as well as experts from major actors in the energy markets. Experts from reforming and emerging economies, such as Russia, China, India and Brazil, contribute to the work. For the work presented here, two reasons are important. The establishment of international energy

experts and commentators use the most recent WEO scenarios as benchmarks for comparison to scenarios from other actors on the energy scene; a recent example is Forbes (2011) discussion of BP and ExxonMobil energy forecasts. The WEO scenarios therefore provide an obvious starting point for the analysis of decarbonisation learning curve. Last but not least, WEO can now rely on the detailed analysis of technology development and deployment in the Energy Technology Perspective project at the IEA Secretariat (IEA, 2010a). Learning curves are important tools in the ETP technology analysis.

Figure 7 shows the global decarbonisation curve for the energy system calculated from historical data and from the three WEO Policies Scenarios. Fitting a learning curve for data up until 1994 provides a learning rate of 20%, nicely following the theoretical prediction. The learning curve is extrapolated and in the following discussion assumed to represent the autonomous decarbonisation rate, ADR. The ADR provides the baseline to which post-94 data and scenario results can be compared. For further comparison, the Breakaway Path considered in IEA (2000) is also provided. The end-point for this Path and for ADR is set to 2060 assuming the economic growth continues after 2035 at the same rate as in the WEO scenarios for the period 2020-2035.

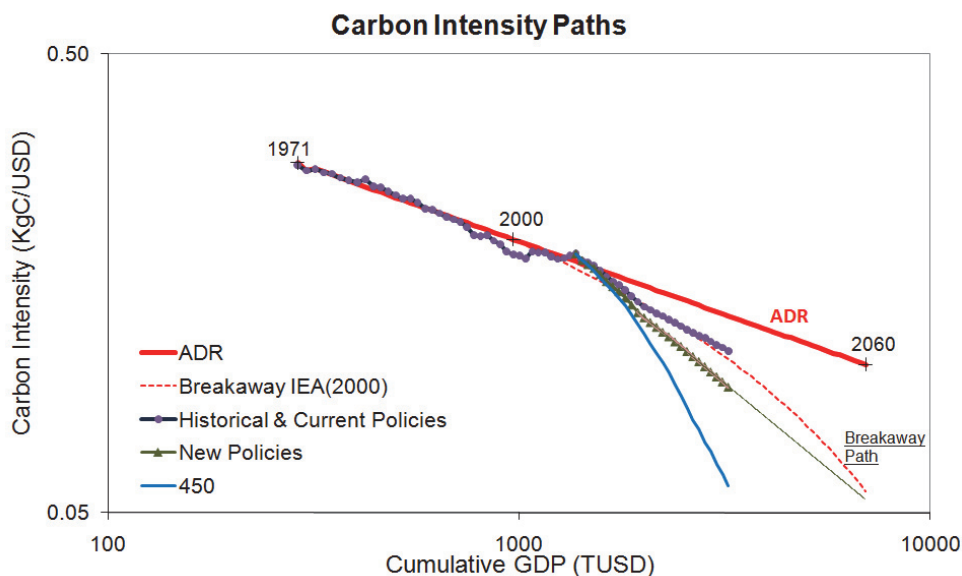


Fig. 7. Decarbonisation of the world economy according to historical data and the three WEO (2010) Policies Scenarios.

Historical data indicate some attempts to break away from the historical ADR in the second half of 1990s. (The “dip” in the curve in the first half of 1990s is a result of the changes in Former Soviet Union and Eastern Europe and not of CO₂ policies.) The breakaway was interrupted in the beginning of 2000s as economic growth took off in major emerging economies such as those of China, India and Brazil. The WEO scenarios assume that break away will resume in the 2010s.

The WEO scenarios are characterized as Current Policies, New Policies and 450 and are briefly described in WEO (2010, p. 79). Current Policies act as baseline “in which only

policies already formally adopted and implemented are taken into account”. New Policies assumes cautious introduction of new measures “to implement the broad policy commitments that have already been announced”. The 450 Scenario limits the concentration of greenhouse gases in the atmosphere to around 450 parts per million of carbon-dioxide equivalent, which should limit the global increase of temperature to 2 degree C. The storyline in WEO (2010) focuses on the New Policies Scenario.

After peaking out and then falling in the 2010s, the decarbonisation curves for the three scenarios appear as learning curves in the period 2020 until 2035, which is the time horizon for the WEO scenarios. The learning curve for New Policies Scenario is extrapolated to the endpoint of the Breakaway Path in IEA (2000. p. 77). This Path provides an interpolation between the Current and New Policies, having the same carbon intensity as the former scenario in 2020 and as the extrapolated New Policies in 2060. The learning rates in the period 2020-2035 for Current Policies, New Policies and 450 Scenarios appear to be 28%, 40% and 67%, that is considerably larger than the ADR. Learning rates of 28% are within the distributions discussed in the previous section and even 40% can be accepted as an extreme value, but 67% is beyond any measured rate for an individual technology. The question arise how these apparently high learning rates should be understood. The following comments reflect on this question from the perspective of technology learning theory.

Today, existing and mature low-carbon and efficient technologies provides a large potential to reduce the carbon intensity of GDP. By 2020 they will still play a major role in the energy system. However, if current policies succeed most of their potential to further *reduce* carbon intensity will be exhausted. The large learning rates after 2020 require deployment of new, more efficient supply, distribution and demand technologies, whose operation provides very-low-to-zero CO₂ emissions. The decarbonisation curve shows the collective results of such deployment.

The theory sees high learning rates as a result of the system adapting to positive perturbations, which in this case must be applied to the whole global energy system. It is possible that e.g., strong support to private R&D (Guellec and van Pottelsberghe, 1993) could spur a 28% learning rate over 15 years and one doubling of cumulative GDP. However, the concerted efforts needed to achieve 40% and even 67% over a long period of time seem beyond what can be expected from the international community. The difficulties are exacerbated by the risk of phase shifts in the learning systems for the new technologies. But technology learning provides an alternative way of achieving the required learning without relying on the inherently unstable medium of positive perturbations.

The period until 2020 could be used to create radical innovations in major parts of the global energy system. Technology candidates for such innovations could be, for instance, thin film or nanotechnology solar PV, deep-sea floating wind parks, 2nd generation biomass, 4th generation nuclear plants, carbon capture and storage technology, smart grids, electric cars, zero energy housing. The radical innovation would reset cumulative output for respective technology learning system, see section 2.2. After resetting the global energy system could rely on the basic, zero learning mode with stable learning rate of 20% equal to ADR to achieve the learning needed.

For Current and New Policies Scenarios, radical innovations are not required in all of the energy system in order to provide the decarbonisation through the basic learning mode. The decarbonisation in the Current policies scenario could be achieved at learning rate 20% provided radical innovations start to be implemented in 45% of the energy system in the last years of 2010s. New Policies Scenario requires radical innovations to be ready to start

deployment in 75% of the energy system. The rate of deployment should follow the same S-curve as is historically observed for the penetration of new technology. 450 Scenario seriously challenges the international community, because it requires a continuous deployment of radical innovations. To understand the magnitude of the challenge one can observe that relying on the basic learning mode of LR=20% to achieve the decarbonisation requires putting in place new radical innovations in more than 80% of the energy system every 5 years. Achieving the 450 Scenario will probably need a combination of public R&D to help create radical innovations and direct support to private industry R&D for the purpose of increased learning rates. Deployment programmes to ensure swift ride down the experience curve to cost-efficiency for new technologies is a fundamental element in all policies.

5. Conclusion

The cybernetic approach to technology learning identifies a spectrum of stable learning modes. The learning rates for these modes are fixed by the theory without any fitted parameters. The basic learning mode has a learning rate of 20%, which explains the clustering of learning rates around this value in existing compilations of measured rates. The distribution of rates around the stable learning modes shows how the learning system adapts to positive or negative perturbations. A simple probabilistic model based on the theory fits distribution of learning rates in available compilations.

The existence of stable learning modes provides the basis for confident extrapolations of learning curves. However, extrapolations require caution. No major changes in the system environment is a condition. Learning curves for technologies moving with learning rates close to a stable learning mode can be extrapolated with larger confidence than technologies where the learning rate deviates considerably from that of a stable mode. The reason is that the first technology shows more resilience to perturbations. The typical example of such technology is solar PV. Because of the risk for phase shifts, extrapolations based on apparent high learning rates have low credibility.

The theory can be applied to analyse and characterize decarbonisation curves. The methodology is demonstrated on the latest scenarios from IEA's World Energy Outlook. The analysis questions whether a low-carbon future can be achieved through continuing incremental technology developments. Radical innovations are necessary in major parts of the global energy system in order to achieve the large decarbonisation required to for a future that can combine a low-carbon energy system with a high-growth economy.

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