Adaptation in Technology Learning Systems

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Abstract
The major finding of the cybernetic approach to technology learning is the 20% learning rate characterizing the eigenbehaviour of the learning system in its unperturbed ground state. This paper explores how double closure makes the system adapt to external perturbations and pressures without losing its autonomy. The ability to adapt, the system's *plasticity*, explains deviations from the 20% rule. Theoretical distributions of learning rates are compared to published distributions of measured learning rates. The analysis reveals policy-relevant differences between distribution of learning rates for energy supply technologies and for non-energy technologies.

1. Introduction

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*. *Experience curves* and *learning curves* measure the results of the process.

Recent high-level policy documents embrace the insights from experience and learning curves into the crucial role of technology learning and market deployment (IEA 2006, 2008; Stern, 2006; EESC, 2009). However, they also point to the large uncertainties in future estimates of learning and that these uncertainties translates into large uncertainties about the resources or learning investments needed to bring the new technologies to break-even with incumbent, high-carbon technologies. A key criticism is that the curves appear to express purely empirical relations between cost, price, or technical performance and cumulative production or use. Theoretical grounding is needed to explain observed learning rates, limit uncertainties in extrapolations and legitimize government deployment programmes.

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 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 cybernetic approach (Wene, 2007; 2008a; 2008b) understands technology learning as *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; Luhman, 2002). The purpose is to ground technology learning in cybernetic theory and explain empirical results about experience and learning curves.

Wene (2007, 2008a) derived learning rates characteristic for an unperturbed system producing for competitive market under equilibrium conditions. The basic learning rate for this system is 20%. Wene (2008b) showed that these theoretical learning rates explained the clustering of learning rates at 20% with a smaller peak at 4-7% for energy technologies observed in published distributions of learning rates. (Dutton and Thomas, 1984; McDonald and Sckrattenholzer, 2000). However, Wene (2008b) does not provide any mechanism explaining the dispersion of learning rates around the theoretical ones.

The purpose of this paper is to extend the cybernetic approach to include dispersion of learning rates. The hypothesis is that the system's ability to adapt, that is its plasticity, explains the observed deviations around unperturbed learning rates. von Förster (1993; 2003) suggest *double closure* as the required process for biological systems to adapt to external perturbations without losing operational closure. This process is applied here to the adaptation of the technology learning system to external perturbations.

The following section recapitulates the basic features of the theory in Wene (2007; 2008a) and extends the theory to the calculations of eigenbehaviour for the perturbed system. Section 3 explores the consequences for distribution of learning rates assuming a simple probabilistic model for external perturbations. Section 4 compares the theoretical results with observed distributions of learning rates.

2. Technology learning as Eigenbehaviour

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 loops reproduced in Figure 1 and defined two operators, C_{SRL} and C^{+}, expressing system performance and the dependence of this performance on cumulative system output. The operators were used to calculate learning rates for the unperturbed case.

In Wene (2007; 2008a) the mathematical form of the experience and learning curves guided the hypotheses on loops and operators. However, both loops and operators can be related to the well-known OADI-SSM[1] model for organizational learning (Kim, 1993; Espejo et al., 1996).

The OADI mnemonic emphasizes learning as a result of self-reflection, i.e., making new Designs after Assessing the Observations of own action, which in this case is the Implementation of previous design efforts. This is consistent with the assumption of operational closure and captured in the three feedback loops in figure 1.

[1] OADI = Observe, Assess, Design, Implement. SSM = Shared Mental Model

The internal and external feedback loops express Implementation-Observation. The external loop closes over the Market, M, and the internal loop over Producing. Together with the third self-reflecting loop, SRL, they provide the *double closure* proposed by von Förster (2003) as the process required for an organism or an organization to modify its behaviour in order to manage environmental perturbations without losing operational closure. The internal and external loops reflect the double closure over production and sales as analyzed by Baecker (1996). The self-reflecting loop represents Assessment-Design and operates on the internal state **Z.**.The internal state sets the transfer function of Producing, i.e. through its actions on the internal state Z the self-reflecting loop determines the performance or the relation between input and output of the learning system. Computing integrates the three loops and should – following Heinz von Förster – be seen as derived from the Italian words *com* (bring together) and *putare* (reflect, contemplate). The self-reflecting loop thus drives the learning of the system but is for its operations totally dependent on the operations in the two other loops.

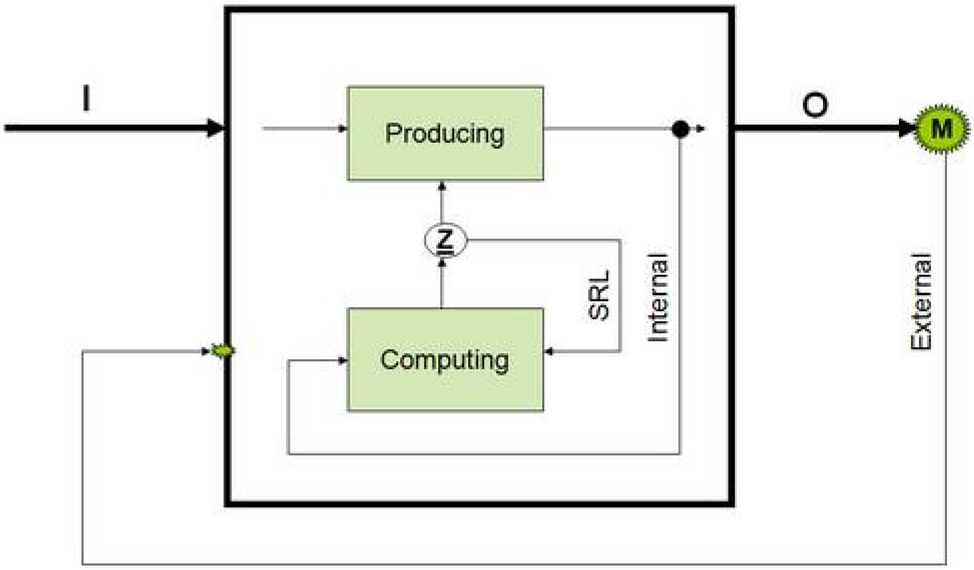

Figure 1. The elements of the technology learning system (modified from Wene (2007))

In the unperturbed case, the external loop carries the urge from the perfect competitive market to improve performance as much as possible but no information about perturbations. It can therefore be seen as a constant factor in this case. The internal loop tracks output from Production. In the mathematical formalism, its actions are described by the operator C^+. The self-reflecting loop sets performance via the internal state, Z, based on its interactions with the internal loop. In the mathematical formalism, its actions are described by the operator C_{SRL}.

The two operators can be interpreted in the OADI-SMM model. In the aggregated universe of the learning curve the C^+ operator provides the corporate memory, the Shared Mental Models, in the OADI-SMM model. The C^+ operator also introduces an internal clock for the learning system. The two steps performed by the C_{SRL} operator maps onto the Assess-Design steps of the OADI model. In the assessment step C_{SRL} forms an image of the previous design attempt. The image is increasingly rotated and enlarged according to the outcome of the C^+ operator. In the design step the image is projected back onto the original vector. The rotation places the image further and further away from the original vector and ensures that the procedure converges to a finite number in spite of the image growing as cumulative output. It is interesting to note Marks-Tarlow's et al. (2002) summing up of several decades of studies of the learning process: "A survey of the work of many developmental psychologists makes it clear that an essential feature of intelligence is the ability to reflexively stand back, as it were, from our own experience and see it objectively" (p.41)

The cybernetic approach is extended by moving to a matrix formulation of the eigenbehaviour equation.

$$\mathbf{\underline{Z}}_{\infty} = \lim_{\tau \to \infty} \begin{pmatrix} C_{SRL} & W_{12} \\ W_{21} & C^{+} \end{pmatrix}^{\tau} \begin{pmatrix} \Delta P_0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} i \\ 1 \end{pmatrix} \qquad \text{(Eq. 1)}$$

The 2/1 matrix is the original system state, $\mathbf{Z}_0$. Following Wene (2007) it is assumed to be the base vectors of the complex Argand plane. ΔP_0 is a constant and equal to the relative improvement in performance for each doubling of cumulative output[2]. τ is the amount of doublings since the system became operationally closed. W_{12} and $W_{21}$are operators representing operations in the external loop. $W_{12} \neq 0$ indicates a double closure between the self-reflecting loop and the external loop and $W_{21} \neq 0$ between the external and internal loops. $W_{12} = W_{21} = 0$ provides the solution for the unperturbed state, which now can be written as

$$\mathbf{\underline{Z}}_{\infty}(n) = \begin{pmatrix} \Delta P_0 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} (2n+1)\cdot\pi & 0 \\ 0 & -i \end{pmatrix} \begin{pmatrix} i \\ 1 \end{pmatrix} \qquad n = 0, 1, 2,.. \quad \text{(Eq. 2)}$$

The eigenvalues for the C_{SRL} operator for the unperturbed case are

$$\boldsymbol{\varepsilon}_{\infty}(n) = (2n+1)\cdot\pi \qquad n = 0, 1, 2, 3, \ldots \qquad \text{(Eq. 3)}$$

providing the following limiting values for the experience parameter[3]

$$E(n) = 1/[(2n+1)\cdot\pi] \qquad n = 0, 1, 2, 3, \ldots \qquad \text{(Eq.4)}$$

The corresponding learning rates are

$$LR(n) = 1 - 2^{-E(n)} \qquad n = 0, 1, 2, 3, \ldots \qquad \text{(Eq.5)}$$

The four first modes of learning are then

LR(0, 1, 2, 3) = 20%, 7%, 4%, 3%, …

A situation with $W_{21} \neq 0$ might seriously upset the internal clock of the learning system and could for instance signal the presence of a radical innovation in the environment. However, it

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[2] 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.

[3] The experience parameter is the exponent E in the experience or learning curve

$$\text{Cost} = \text{constant} \times (\text{cumulative output})^{-E}$$

will not explain dispersion of learning rates around the values in equation (5). In this paper the focus is on W_{12} assuming $W_{21} = 0$. Through double closure the W_{12} operator may modify the eigenvalues for the C_{SRL} operator. We assume that any perturbation from the market is synchronised to the output from the system. ΔP_0 provides a measure of the strength of the perturbation and W_{12} can be parametrized as

$$W_{12} = \alpha(\tau) \cdot \Delta P_0 \cdot C^{+} \qquad \text{(Eq.5)}$$

Wene (2010) provides solutions of equation (1) for negative and positive values of $\alpha(\tau)$, and for different durations of the perturbations in system time τ, e.g., the perturbation being permanent or transient. The solutions turn out to be quite different for negative and positive α-values. For negative α-values the eigenvalues for C_{SRL} during the duration of a perturbation of fixed strength converge to

$$\boldsymbol{\varepsilon}_{\infty}(n, \alpha) = (2n + 1) \cdot \pi - \alpha \qquad n = 0, 1, 2, 3, \ldots \qquad \text{(Eq. 6)}$$

As expected, a negative perturbation will thus reduce the learning rate. Likewise, equation (6) characterizes the behavior 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 eigenvalues of CSRL converges to

$$\boldsymbol{\varepsilon}_{\infty}(n, \alpha) = (2n + 1) \cdot \pi + \alpha \qquad n = 0, 1, 2, 3, \ldots \qquad \text{(Eq. 7)}$$

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. 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 lose its own learning ability if exposed to a free positive learning contribution. The phase shift has consequences both for the analysis of learning rate distributions and for the possibility to increase learning rates by public R&D.

3. Double closure leads to a dispersion of learning rates

Equations (6) and (7) indicate that the interactions between the self-reflecting and external loops may lead to a dispersion of values for ε around the eigenvalues given by equation (3). However, due to the phase shift a symmetric distribution of positive and negative perturbations may not result in a symmetric distribution of ε around the eigenvalues for the unperturbed case. The dispersion is explored with the help of a simple probabilistic model for the occurrence of perturbations. The external perturbations will be called FEPs[4], the acronym standing for Features, Events and Processes in the environment requiring adaptation in the learning system. Wene (2010) provides taxonomy of FEPs.

[4] The acronym “FEP” (feature, event, process) is used here to denote the individual elements forming or influencing the technology learning system. The term “FEP” was originally introduced in the ‘Sandia Methodology’ to analyse the safety of repositories for nuclear waste (Cranwell et al. 1990, Chapman et al., 1995).

The number of doublings in cumulative output, τ, provides an internal clock for the system. The parameter τ is referred to as system eigentime or system time. The model assume positive and negative FEPs to be independent and randomly distributed but their mean intensities are assumed constant in system eigentime and given by λ_{pos} and λ_{neg}, respectively. This means that positive and negative FEPs are Poisson distributed around their respective mean intensities. It is further assumed that all FEPs have the same absolute strength, S_{FEP}, measured in ΔP_0. At any eigentime, τ, the active FEPs can be added together to yield the value of α(τ), that is:.

$$\alpha(\tau) = A^{+}(\tau) \cdot S_{FEP} \;\; - \;\; A^{-}(\tau) \cdot S_{FEP} \; = [A^{+}(\tau) - A^{-}(\tau)] \cdot S_{FEP} \qquad \text{(Eq. 8)}$$

$A^{+}(\tau)$ and $A^{-}(\tau)$ are the number of active FEPs at time τ. Their distribution depends on the mean intensities and on the distribution of FEP duration. The distribution of α-values can be obtained, e.g. through a Monte-Carlo simulation. However, to retain an analytical solution to equation 8 further simplifications are introduced relying on the idea that the production of external FEPs is a Poisson process.

For the simplified, analytical model we assume that all FEPs that are active during the measuring period are present already at the beginning of the period and that their duration is at least equal to the total measuring period. This means that the difference $[A^{+}(\tau) - A^{-}(\tau)]$ is a fixed whole number independent of eigentime providing a constant value of α for the whole measuring period. Note that α is a discontinuous variable. From equation 8 it follows that it can only take on values that are equal to the absolute strength times the difference between the number of negative and positive FEPs. The probability function for α is given by the probability function for $[A^{+} - A^{-}]$, which can be calculated using the standard convolution formula (see e.g., Gut, 1995, p. 10-12),

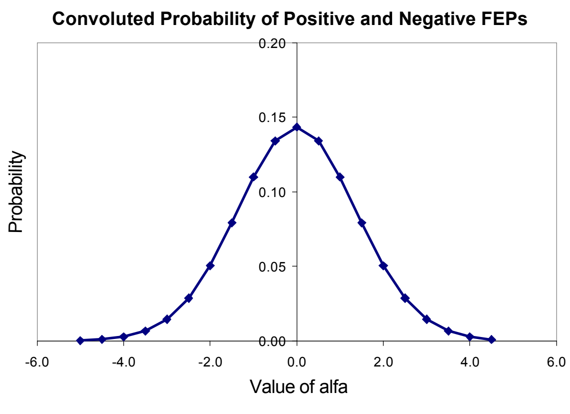

Figure 2. Probability of α

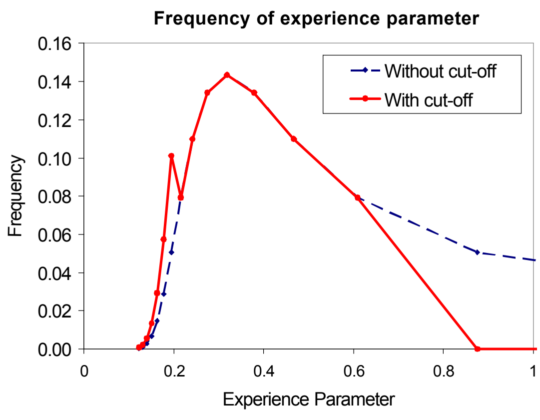

Figure 3. Frequency of E

Figure 2 shows the probability function of α-values for $\lambda_{pos} = \lambda_{neg} = 4$ and $S_{FEP} = 2$. With equal intensity for negative and positive FEPs the distribution is symmetric around α = 0 The literature reports learning rates and experience parameters and we choose in the following to discuss results in terms of experience parameters, which is the parameter fitted to obtain an experience or learning curve. The question is how the model in figure 2 translates into frequencies of experience parameters. Following equations (4) and (6), the experience parameter around zero learning mode for negative and small positive α is given by

$$E_{FEP}(0) = 1 / (\pi - \alpha) \quad \text{(Eq.9)}$$

However, large positive α will induce a phase shift after which the system will be characterized by an experience parameter equal to

$$E_{FEP,PF}(0) = 1 / (\pi + \alpha) \quad \text{(Eq. 10)}$$

In the simple model the phase shift will be simulated by a cut-off in α, for which the calculations in Wene (2010) suggest the value 2, i.e.

$$\alpha_{c\text{-}o} = 2 \quad \text{(Eq. 11)}$$

The cut-off means that for $\alpha \leq \alpha_{c\text{-}o}$ the experience parameter is given by equation (9) but for $\alpha > \alpha_{c\text{-}o}$ the experience parameter is calculated from equation (10). Figure 3 shows the frequency distribution for the experience parameter following from the α-probability function in figure 2.

As expected from equation (4), a symmetric distribution of α-values will lead to a strongly asymmetric frequency distribution for the experience parameter. The phase flip will reduce occurrences with higher E-values. All occurrences corresponding to $\alpha > \alpha_{c\text{-}o}$ will instead appear in the sharp peak below E = 0.2 or learning rate less than 13%. Empirical evidence for phase flip will be discussed in the following section, which will also study how well the simple model can reproduce features of measured distributions.

4. Comparison theoretical and empirical distributions

The simple model in the previous section provides the analyst with three parameters to fit the model to a measured distribution, the intensities λ_{pos}, λ_{neg} and the strength S_{FEP}. The fourth cut-off parameter can be varied within a narrow band of values constrained by equation (1).

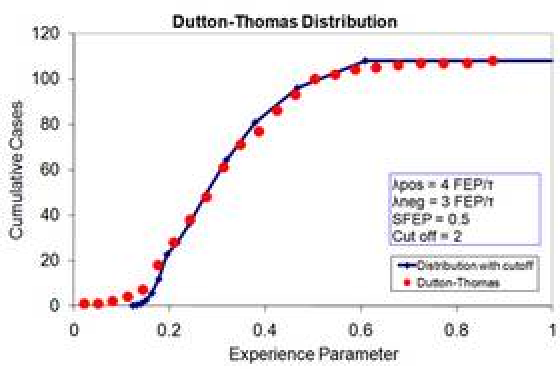

Fig. 4. Probabilistic model fitted to Dutton and Thomas (1984) distribution

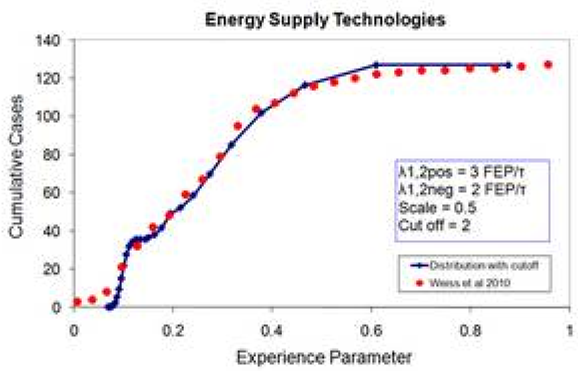

Fig. 5 Probabilistic model fitted to Weiss et al. (2010) distribution

Figures 4 and 5 show fits of the simple probabilistic model to two 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 technologies based on market prices. This distribution shows the dispersion of learning among industries rather than among enterprises.

For the comparison the learning rates have been recalculated to experience parameters using equation (5). The results of the probabilistic model permit some initial observations.

The first observation is that double closure explains the observed dispersion of learning rates or experience parameters. The probabilistic model based on the extended cybernetic theory for technology learning provides an equally good fit to *both* distributions. However, theoretical analysis also points to some interesting differences between the two distributions. Some of these can be explained by different learning systems, in first case enterprises in second case whole industries, but other differences require further studies.

The two distributions are fitted assuming the same strength, S_{FEP}. However, the intensities λ_{pos}, λ_{neg} are 20-30% lower for the Weiss et al. (2010) distribution compared to the Dutton and Thomas (1984). This means that the dispersion in α-values is less for the distribution of industry experience parameters than for individual enterprises. Wene (2008b) pointed out that this result follows from a central theorem in mathematical statistics, namely that the variance of means is less than the variance of the total distribution. Weiss et al (2010) distribution 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 (Gut, 1995, pp. 173-177) would indicate that Weiss et al. (2010) distribution represent averages over 2-3 firms, however, more detailed probabilistic models are necessary to verify this.

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 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 technologies cannot be explained without higher order learning. The theoretical curve in figure 5 only shows 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) speculates over the causes for the appearance of higher order learning. One reason is methodological. The chosen system boundaries may be too narrow to provide full operational closure. For the analysis of wind energy, increasing the system boundaries from wind turbines to complete wind parks tends to bring results in accordance to those expected for zero order learning. But there are other reasons with consequences for energy technology policy. Many energy supply technologies are strongly regulated and especially fossil and nuclear technologies are exposed to insistent and changing FEPs, e.g., regarding emissions and safety. This may overtax the system's ability to adapt through double closure and instead force the system into slower learning eigenbehaviour. Another environmental factor is government R&D. The purpose is to produce knowledge to increase learning, but systemically it represents a positive FEP risking a phase shift. Insistent public R&D on incremental innovations for technologies competing in the market may relax the internal learning incentives so much that the system migrates to a slower learning eigenbehaviour. Further studies should be important to determine the roles of government R&D versus government deployment programmes to accelerate development of cost-efficient low-carbon energy technologies.

5. Conclusions

In the experience and learning curve literature, reference is often made to the tendency of learning rates to cluster around 20%. The cybernetic theory verifies this observations and establish LR = 20% as the basic, zero learning mode of an operationally closed learning system. The present paper extends the theory to understand the dispersion of learning rates around 20% and around higher learning modes predicted by the theory.

The claim is that the extended cybernetic theory explains fundamental aspects of the technology learning phenomenon, thus improving the usefulness of experience and learning curves in designing efficient deployment programmes and in analysing low-carbon energy scenarios.

The paper identifies issues for further studies both to improve methodology and to clarify policy implications. Understanding the conditions for operational closure is important in setting the system boundaries when measuring experience and learning curves, but also for designing efficient deployment programmes. This will require organisational analysis of the learning system.

Another issue concerns the apparent lower learning rates for learning systems on energy supply technologies compared to non-energy technologies. This raises the questions of the influence of regulations but also of the risk that government sponsoring of short-ranged R&D in the hope of increasing learning may be counterproductive. A future key issue will be the role of government R&D versus deployment programmes.

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