ELSEVIER

Energy Policy 34 (2006) 1645–1658

ENERGY POLICY

www.elsevier.com/locate/enpol

Technological learning and renewable energy costs: implications for US renewable energy policy ☆

Peter H. Kobos[a,*], Jon D. Erickson[b], Thomas E. Drennen[a,c]

[a]*Office of the Chief Economist, Sandia National Laboratories, P.O. Box 5800, MS 0749, Albuquerque, NM, 87185, USA*
[b]*Rubenstein School of Environment and Natural Resources, University of Vermont, Burlington, VT, 05405-0088, USA*
[c]*Department of Economics, Hobart and William Smith Colleges, Geneva, NY, 14456, USA*

Available online 22 January 2005

Abstract

This paper analyzes the relationship between current renewable energy technology costs and cumulative production, research, development and demonstration expenditures, and other institutional influences. Combining the theoretical framework of 'learning by doing' and developments in 'learning by searching' with the fields of organizational learning and institutional economics offers a complete methodological framework to examine the underlying capital cost trajectory when developing electricity cost estimates used in energy policy planning models. Sensitivities of the learning rates for global wind and solar photovoltaic technologies to changes in the model parameters are tested. The implications of the results indicate that institutional policy instruments play an important role for these technologies to achieve cost reductions and further market adoption.
Published by Elsevier Ltd.

Keywords: Learning by doing; Renewable energy costs; Research expenditures

1. Introduction

Changes in the electricity sector, international concern over climate change, and domestic concerns about energy security provide opportunities for renewable energy sources to increase their market share. Forecasts of renewable energy market penetration rates range from highly optimistic judgments to historical trend extrapolation. One particular analytical shortcoming is the linkage between research, development and demonstration (RD&D) investment and future renewable energy production costs. Without institutional support, emerging energy technologies are limited by their financial costs from penetrating the commercial market. RD&D expenditures allocated today will shape the development pathways for energy production methods for decades to come (Nakićenović et al., 1998; Margolis and Kammen, 1999a).

Contrary to growing energy security concerns, the renewable energy sector in the US continues to suffer from declining real public RD&D investments (Margolis and Kammen, 1999a, b; McVeigh et al., 1999). Fig. 1 illustrates US government RD&D expenditures for solar photovoltaic (PV) and wind compared with the 26 International Energy Agency (IEA) member countries. Due in part to minimal RD&D investment and continued subsidies of fossil fuel and nuclear technologies, the US installed capacity of renewable power has remained far below levels analysts believed would be in place by the early 21st century (McVeigh et al., 1999). Wind power generating capacity, for example, was projected by the Committee on Nuclear and Alternative Energy Systems in 1979 to reach 45,000 megawatts

☆This paper is based on Kobos (2002b), Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy under Contract DE-AC04-94AL85000.

*Corresponding author. Tel.: +1 505 845 7086;
fax: +1 505 844 3296.
E-mail addresses: phkobos@sandia.gov (P.H. Kobos), jon.erickson@uvm.edu (J.D. Erickson), drennen@hws.edu (T.E. Drennen).

0301-4215/$ - see front matter Published by Elsevier Ltd.
doi:10.1016/j.enpol.2004.12.008

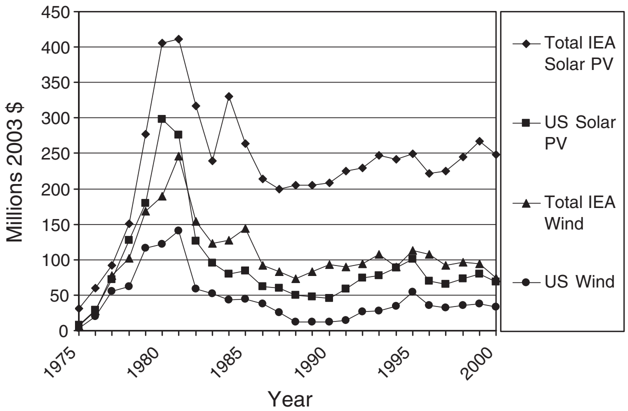

Fig. 1. Government RD&D expenditures of IEA countries and the US for wind and solar PV technology (IEA, 2002; EIA, 2001; BEA, 2004).

(MW) by 1995 and 140,000 MW by 2000 (McVeigh et al., 1999). Analysts in the private sector produced similar scenarios of installed capacity for 2000 ranging between 17,200 and 240,600 MW (GE, 1977). The actual wind power generating capacity in the US in 1995 and 2000, however, was only 1770 and 2554 MW, respectively (AWEA, 2001; IEA, 2001). Relative to the capacity in 2000, the US saw strong growth in wind capacity installations with total capacity reaching 6366 MW by 2003 (BTM Consult ApS, 2004).

Fig. 2 illustrates the dramatic declines in US RD&D investment for energy technologies, both renewable and nonrenewable, during the 1980s. The renewed free-market ideology of this era called into question the need for continued federal support of energy technologies in general. However, the market domination of nonrenewable energy technologies was reinforced by electricity price subsidies and declines in world fuel prices, further biasing RD&D investments toward tried and true technologies. Analysts arguing for the merits of energy RD&D for nonrenewable over renewable sources often base their argument on energy price (e.g. $ per kilowatt-hour (kWh)) reductions rather than production cost (e.g. $ per kilowatt) improvements. This fails to consider the significant role that price subsidies and falling fossil fuel prices had on traditional energy prices—leading many to denounce federal renewable energy technology RD&D policies (McVeigh et al., 1999).

The nonrenewable and nuclear bias is most striking in Fig. 3. Annual RD&D expenditures have decreased for all energy technologies; however, the *cumulative* nature of RD&D-derived knowledge has led in part to the limited utility scale deployment of renewable energy technologies over the last few decades.

The leadership position the US once enjoyed in renewables in the wake of the 1970s oil crises was lost in the face of low real oil and gas prices and a subsequent lack of political priority. Japan is largely dominant in the PV market, with the US PV

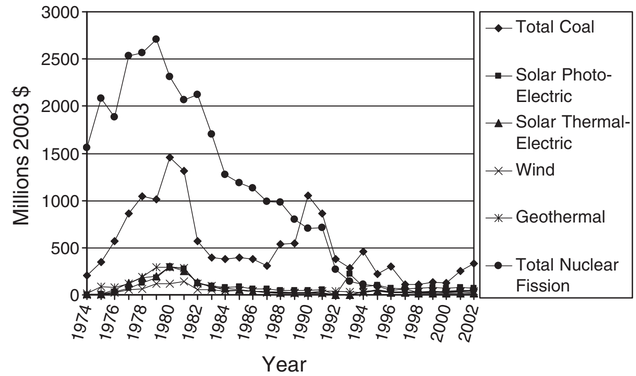

Fig. 2. Select annual energy RD&D allocation in the US (IEA, 2002; EIA, 2001; BEA, 2004).

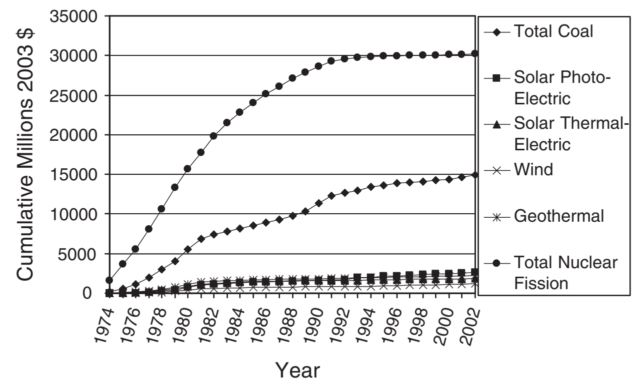

Fig. 3. Select cumulative energy RD&D allocation in the US (IEA, 2002; EIA, 2001; BEA, 2004).

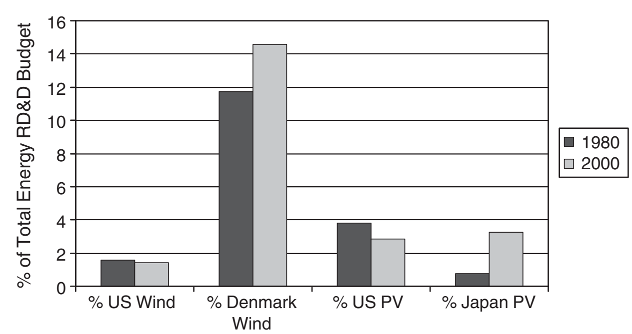

Fig. 4. Wind and PV energy RD&D in the US, Denmark, and Japan (IEA, 2002; EIA, 2001).

industry having moved toward exporting technology to developing countries, low power niche applications, and other remote power applications (Chapman and Erickson, 1995). Following the ‘‘Great California Wind Rush’’ of the 1980s (Asmus, 2001, p. 13), the US also lost considerable market share in wind power to northern Europe, particularly to Denmark. Fig. 4 illustrates the relative levels of energy RD&D these technologies received in the US, Denmark and Japan.

In both Japan and Denmark, the successful application of PV and wind energy production is due, in part, to sustained public investment (Watanabe, 1995a; Neij, 1999). Japan's Ministry of International Trade and Industry, for example, pursued a technology policy that stimulated industry-level innovation for PV. By applying federal RD&D funds more directly to industry, Japan created a classic example of a "virtuous cycle" between RD&D, market growth, and production price reduction (Watanabe et al., 2000, p. 300). Denmark followed a similar pathway by sustaining government support in a myriad of forms for private industry (Christiansson, 1995; Neij, 1997, 1999).

To explore this relationship between RD&D investment, energy cost reduction, and market penetration, this paper estimates energy cost as a function of cumulative installed capacity (a learning by doing factor) and cumulative RD&D expenditures (a learning by searching factor). The introduction of RD&D within a two-factor experience curve is a relatively new development in the traditional learning by doing literature, experiencing a flurry of recent research (e.g. Miketa and Schrattenholzer, 2004; Barreto, 2001; Cory et al., 1999; Kobos, 2002a, b, c; Kouvaritakis et al., 2000; Schrattenholzer, 2000; Schrattenholzer and Kobos, 2000; Watanabe, 1995a, b, 2000; Watanabe et al., 2000, 2001; Wene, 2000). This study builds, in particular, on the Kouvaritakis et al. (2000) model, incorporating an extensive renewable energy technology database developed with the wind and solar energy departments at Sandia National Laboratories in Albuquerque, New Mexico.

Results yield experience curve parameters for cumulative capacity and RD&D expenditures, estimated with both a time lag between initial RD&D investment and the first occurrence of cost reductions, and an RD&D knowledge depreciation factor. This second effect can also be considered as a rate of forgetting (Miketa and Schrattenholzer, 2004; Schrattenholzer and Kobos, 2000; Kouvaritakis et al., 2000; Argote, 1999; Li and Rajagopalan, 1998). The experience curves form the basis for scenario analysis of cost reductions and market penetration for wind and PV technology, and a comparison to the Renewable Energy Technology Characterizations report (EPRI and DOE, 1997) and other learning curve-based, policy-oriented projects.

2. Modeling learning in energy production systems

Institutions are broadly defined by economists and innovation theorists as social, political, and economic organizations that determine the working environment for systems to develop within. Institutional economists emphasize the role that institutions play on the outcomes of economic operations more than their neoclassical-school counterparts (Edquist and Johnson, 1997; Hodgson, 1989; Horner, 1989, Myrdal, 1944, 1972). Ayres (1957), as cited by Samuels (1995) described the framework of institutional economists:

> The crux of the institutionalist position, its 'object of dissent', is 'the conception of the market as the guiding mechanism of the economy, or, more broadly, the conception of the economy as organized and guided by the market. It simply is not true that scarce resources are allocated among alternative uses by the market. The real determination of whatever allocation occurs in any society is the organizational structure of that society—in short, its institutions.' (p. 571)

Indeed, Nelson (1995) reiterates how important an industry's working environment is when examining technology development and cycles. For instance, the direction of domestic technology innovation can be influenced by knowledge spillovers due to international trade, the flexibility and ease of information flow from the university system, and the structure and patent-making ability of the legal system. These institutional dynamics can vary widely across countries, both within and across different development levels. As such, global rates of technology development do not always imply similar rates of technology diffusion in particular domestic markets.

The types of institutions influencing innovation, and ultimately technology diffusion, have been categorized as horizontal, nonmarket, and vertical (Reddy et al., 1991). Horizontal institutions include those in which large technical interdependencies exist between products or organizations. Positive feedbacks can emerge between horizontal institutions as, for instance, RD&D in one industry can lead to innovation or increased market potential in the other. In renewable energy technology, horizontal manufacturing structures may be necessary to successfully penetrate the market. For example, energy efficient home construction would benefit from well-designed solar thermal water heating systems.

Nonmarket institutions are designed for goals not explicitly focused on short-run profits. These include professional societies, governmental agencies, and university-level research centers. These institutions often provide the necessary basic research and generic market promotion for incubating new technologies. They are often designed as subsidies to industry development and their effectiveness is often dependent on political goals and agendas when "society has found it necessary to supplement the usual market mechanism by additional institutions" (Mokyr, 1990, p. 181). For example, the political environment behind Japanese government support for PV innovation was critical in developing the inter-industry partnerships, basic public research, and broad-based market promotion for this fledgling industry (Watanabe et al., 2000). In particular, universities provide the basic research that benefits all industry participants, and serves as the training ground for future scientists and industry leaders. The generation of this 'human capital' has been an important component of more recent theories of economic growth (Lucas, 1988; Mankiw et al., 1992).

Lastly, vertical institutions strive to solidify the connection between research and innovation assets and a tangible product. For instance, the development of the defense sector, from the mine to the missile, is a prominent display of a vertical institution at work. G.N. von Tunzelmann (1995) describes how the defense sector of the former Soviet Union successfully used a linear, vertical segmentation (institution) model. The success of this sector relied heavily on the mission-oriented, political underpinning of the organization, and the unique willingness of both the defense sector and political powers to fill the gaps in civilian sectors necessary to induce user–producer interaction.

Government and other organizing entities can often work to administer a coordination system. Fig. 5 illustrates a conceptual framework for learning between individuals (e.g. workers and groups of workers) and the organization as a whole. The solid arrows represent flows of knowledge spillovers; the dashed arrows represent knowledge feedbacks. These feedbacks reinforce the role of knowledge stock solidarity (standardization) and quality control. For example, a knowledge spillover or 'feed forward' from the organizational level to the individual level can include implicit on-the-job training. While a feedback from this knowledge transfer (generation) would include suggestions and discussions, these individuals have with the management directing the organizational training programs and work environments.

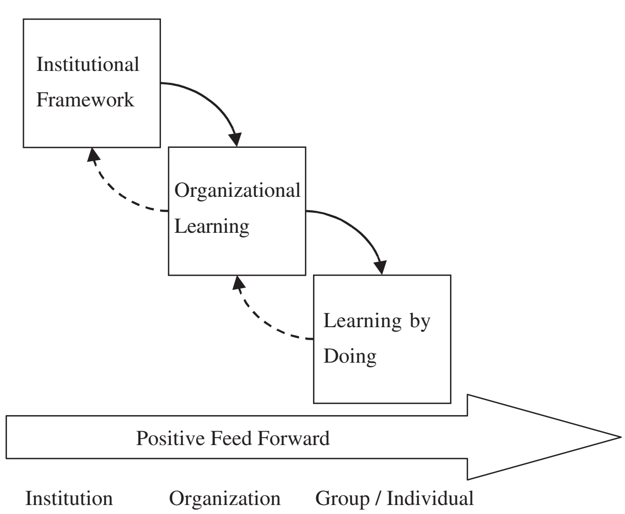

Fig. 5. A dynamic process of organizational learning (adapted from Crossan et al., 1999).

Along these same lines, organizations, firms, and other actors learn how to produce goods and services more efficiently over time as actors move through a "learning cycle" (Zangwill and Kantor, 1998, p. 910). A learning cycle takes place over a period of time where management takes action to improve the production process, observe the results of the action, and learn from these observations to further improve the process. For energy technology this means the gradual adoption (or acceptance) of a standard method of energy technology production, and coordinating the mechanisms between various institutions where each may be on a unique learning trajectory (Cohendet and Llerena, 1997).

Governments and laws may be one institution that can promote the formation and stability of these links, but so may professional organizations, professional societies, university to business linkages, and other collaborative efforts to consolidate research efforts (Reddy et al., 1991). Specifically, the long delay of direct returns from RD&D and the public good nature of knowledge spillovers can create a significant disconnect between their costs and benefits. This disconnect calls for more formal feedback structures between RD&D producers and consumers (Sloth and Lundvall, 1997). The formal structures of government action and the existence of contracts are two methods used to establish and maintain links between the actors in a network or general system. Without these formal structures guarding the links, the necessary levels of efficiency may not materialize through learning and collaboration for a given technology. A technology and the system that promotes it may then enter a vicious cycle, or no cycle at all, whereby market diffusion may prove impossible.

Market diffusion for emerging energy technologies—the last step in the product chain from concept to consumer—is also a dynamic process with feedback effects. Sonis (1992) thoroughly describes the interrelated nature of market diffusion, competition, and dynamic processes through several major types of factors: the adopters, entrepreneurs, alternatives to the commonplace, and the existence of an active environment. The adopters, in the context of renewable energy, are both the consumers and producers of the energy. The consumers must demand the energy for 'green' purposes, economic incentives, or other reasons. The producers (often sharing the role of the entrepreneurs) must convert the innovations in renewable energy technology into viable choices for consumers to use. In short, the entrepreneurs must produce a viable set of alternatives to the mainstream methods of energy production that can compete in the face of price-conscious consumers for electricity generation. The presence of a conducive, active environment for this process to take place contributes to successful market diffusion. Institutional feedbacks contribute to the technology's diffusion throughout the market by moving to or keeping the technology in a virtuous cycle.

Lastly, market diffusion is not preordained simply by the presence of a network; whether through RD&D, governmental initiative, or inter-industry ties (Arthur, 1988, 1989). Robertson et al. (1996) argue that while networks can, and often do, allow ample opportunity for market diffusion of innovative technologies, the role of *strong* information links between the industries are crucial to allow for such opportunities to materialize. Without durable links between the nodes of the network, relatively weaker institutional constraints may be sufficient to break the links between innovators and erode the cyclic nature of the system. Specifically, if RD&D funding and information flows are not strong enough between, for example, national energy laboratories in the US, then nonrenewable energy interests and politics may be sufficient to erode learning effects, and consequentially the market potential of renewable energy technologies for the US energy market.

2.1. Learning by doing and measuring technology cost trajectories

Conceptually, the progression of cost innovations through time move in steps due to technological breakthroughs at the component level, while at the same time progressing smoothly when analyzing the technology as a whole. A common framework used to conceptualize the production cost and market price of a technology through time is a type of cost curve, illustrated in Fig. 6. The declining cost trend represents incremental cost improvements, or 'incremental innovation'. In contrast, the four general stages of a technology's pricing development include the development, price umbrella, shakeout and stability stages.

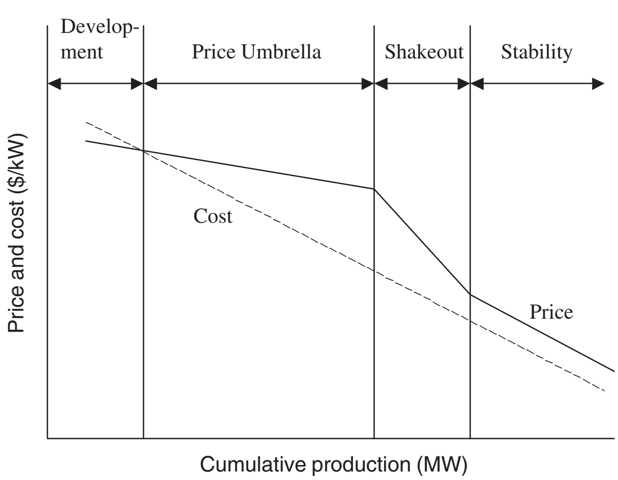

Fig. 6. Conceptual distinction between energy production cost and the subsequent price (adapted from Boston Consulting Group, 1968).

These represent potential trends in the difference between the technology's cost and the market pricing strategy for the developing industry. Because the underlying cost trend is believed to be relatively stable, as well as the price/cost ratio, cost curves are amenable to deterministic modeling.[1]

An evolving technique to estimate these cost curves is learning or experience curve analysis. An experience curve describes the relationship between cumulative output and per unit cost of a technology. As the cumulative production capacity increases, the producer learns how to streamline the manufacturing process thereby lowering the cost per unit of output. This type of relationship between quantity and costs was first discussed by Wright (1936). Additionally, the notion of 'learning by doing' was stated explicitly by Arrow (1962) and also builds on the work of the Boston Consulting Group (1968). Many economists have since built on this type of framework. Specifically, Muth (1986) and Venezia (1985) analyzed theories of the experience curve based on the random search of technological possibilities within a given population. Recent contributions by Miketa and Schrattenholzer (2004), McDonald and Schrattenholzer (2001), Schrattenholzer (2000), Wene (2000), Watanabe (1995b), Watanabe et al. (2000), Neij (1997, 1999), and others have applied the learning curve framework to energy technologies.

In this context, the following equations describe the methods used to quantify the learning processes observed in solar and wind energy. Eq. (1) quantifies a standard experience curve relationship between cumulative capacity of technology i (CCi) and per-unit cost (Cost$_{t,i}$), where Y_i captures capital costs at initial levels of installed energy capacity.

$$Cost_{t,i}(CC_i) = Y_i * CC_{t,i}^{-a_i}. \tag{1}$$

Cumulative capacity as a single variable represents several cost reducing variables, including materials research, economies of scale, increasing skill in the labor force, and implementing an overall RD&D investment. The parameter a_i captures a technology-specific elasticity estimate. A progress ratio ($0<PR_i<1$) and corresponding learning rate (LR_i) can then be calculated as:

$$PR_i = 2^{-a_i}, \tag{2}$$

$$LR_i = 1 - PR_i. \tag{3}$$

A progress ratio of 80% implies that for every doubling of capacity, costs per unit of output decrease

[1]The price may also be modeled as a proxy for technological learning, however, known or assumed profit margins and the 'breaks' between the market stages including the development, price umbrella, shakeout and stability stages are important to recognize.

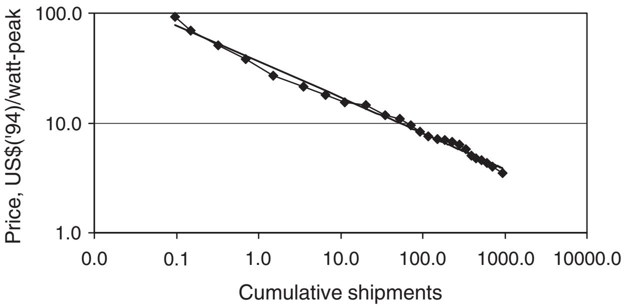

Fig. 7. An experience curve for PV modules (adapted from Harmon, 2000).

by 20%.[2] This represents a learning rate, or 'learning by doing'. For example, Fig. 7 highlights the results of an experience curve estimate for PV modules worldwide from an analysis by Harmon (2000) where the learning rate was estimated to be 20.2%. This learning rate representation has become a standard in the literature to represent experience curve phenomena, which generally allows one to compare learning processes between studies.

The independent variable of $\mathrm{Cost}_{t,i}$ can be measured as production cost, installed cost, user cost, or in some cases price. Each has its own assumptions that are important to clarify for cross-technology and cross-country comparisons. For this study, a capital cost estimate measured as dollars per kW (kilowatt) is used. Energy cost in dollars per kWh is also a popular metric used to track the cost of energy generation between technologies. This cost metric, however, is problematic due to a large variance in the financial assumptions built into the levelized energy cost figures. For instance, the discount rate, system efficiency, system lifetime, and daily power output can vary dramatically across studies. A $/kW metric is not without inconsistency. Government subsidies and other strategic market influences clearly distort the role of technological progress in the evolution of electricity costs. However, a $/kW metric most closely captures the nature of learning by doing in the production process as postulated by Arrow (1962).

2.2. Two factor experience curves: technological learning and the introduction of RD&D

Until recently, the concept of learning in the experience curve framework represented an informal composite of variables that generally reduce production costs (Neij, 1997). Clearly the reduction of costs can occur through a number of separable parameters. The effect of RD&D investment on cost reduction (and ultimate market diffusion) through a knowledge stock effect has been of particular interest from a public policy stance. McDonald and Schrattenholzer (2001), in complementary fashion to Watanabe (1995a, b; 1999) and Watanabe et al. (2000), call for the inclusion of an RD&D proxy on cost estimates. Additionally, the Union of Concerned Scientists (1999) note, "most renewable technologies are likely to experience cost reductions as a result of not only learning … but also of research and development and of growth in the international market" (p. 8).

In the past, policy makers have estimated an RD&D effect as a constant percentage of total expenditures allocated to RD&D with a limited focus on the learning phenomenon. In contrast, Miketa and Schrattenholzer (2004), Klaassen and Miketa (2002), Kobos (2002a, b, c), Criqui et al. (2000), Kouvaritakis et al. (2000), Cory et al. (1999) and others explicitly incorporate R&D or RD&D expenditures into a two-factor experience curve in a similar manner to that of cumulative capacity in the one-factor experience curve.

Eq. (4) illustrates the two-factor experience curve relationship between cumulative capacity of technology i ($CC_{t,i}$) and cumulative knowledge stock of technology i ($KS_{t,i}$) on the per-unit cost ($Cost_{t,i}$).

$$Cost_{t,i} = Y_{t,i} * (CC_{t,i}^{-a_i} * KS_{t,i}^{-b_i}). \tag{4}$$

Taking the logarithm of this functional form specifies both a learning by doing elasticity (a_i), and a learning by searching elasticity (b_i).

Including RD&D directly in the learning function presents several analytical challenges. First, RD&D data often prove difficult to accurately measure and obtain. Industry-specific data, in particular, is scarce. State and national-level data is available from the National Science Foundation, the Energy Information Administration (EIA), the International Energy Agency (IEA), and the various national US energy laboratories including Sandia National Laboratories and the National Renewable Energy Laboratory. The EIA, for example, maintains data on the annual additions of generating capacity for both renewable and nonrenewable energy technologies. They also maintain data on state, national, and worldwide energy prices, estimated supply and demand of energy by type, and a large amount of literature specific to RD&D and energy technologies. Additionally, the IEA maintains a country-specific energy RD&D database available on their website (IEA, 2002).

A second analytical challenge is that RD&D from past years is likely to have much less influence on cost reductions of present technology. Technological turnover in the form of modifications or complete restructuring must be addressed. For example, the RD&D expenditures and applicable knowledge gained

[2]The relative cost for each doubling of cumulative installed capacity is (modified formula adapted from Neij, 1997) $(Cost(CC)_1 - Cost(CC)_2)/Cost(CC)_1 = 1-((Y^*(2CC_1)^a)/(Y^*CC_1^a)) = 1-2^a$.

in developing optimal silicone cell fabrication techniques for solar photovoltaics would not offer much additional, new knowledge, or cost reductions to more recent developments in solar PV systems (Ruby and Gee, 2001). Therefore, a knowledge depreciation factor or "rate of … technology obsolescence" should be included in the learning effects on cost reductions (Watanabe et al., 2000, p. 301; Argote, 1999). Li and Rajagopalan (1998) also suggest using knowledge depreciation in learning curve analysis. They hypothesize the wide range of learning rates between and even within industries may be due to differing knowledge depreciation rates. Additionally, the length of time lags between RD&D and commercial deployment is of significant interest to both industry and academia (Miketa and Schrattenholzer, 2004; Li and Rajagopalan, 1998; Watanabe et al., 2000). McDonald and Schrattenholzer (2001) emphasize the importance of the knowledge depreciation rate and location on the experience curve for a firm when forecasting cost reductions. For example, a technology such as wind energy can have a doubling of capacity and subsequent potential cost reductions within a shorter time frame than could coal-fired power plants, even if the two learning rates are the same.

To help account for the dynamic nature of RD&D investment, a time lag between initial RD&D and subsequent cost reductions is included in this analysis. Necessary econometric tests are utilized to evaluate potential serial correlation and multicollinearity issues common to time series analyses. Eq. (5) illustrates the annual calculation for the technology-specific knowledge stock at time $t+1$ for technology i based on the knowledge stock at time t, a rate of knowledge stock depreciation (ρ), and RD&D investment lagged by the time between innovation and commercialization (g).

$$KS_{t+1,i} = KS_{t,i} * (1 - \rho_i) + (RDD_{t-g,i}). \tag{5}$$

Parameters of Eq. (4) are estimated assuming a Cobb-Douglas functional form in order to maintain a consistency with the one-factor experience curve. The choice of the Cobb–Douglas form, despite its ability to easily analyze quantitative relationships, has sparked some debate (Kouvaritakis et al., 2000; Schrattenholzer, 2000). Therefore, the choice of this functional form should be considered a starting point for a more complex, or modified interpretation of RD&D in the learning process.[3]

[3]To its credit, a learning by doing framework using the Cobb-Douglas functional form assesses the cost reductions for the average change in installed capacity or knowledge stock, analogous to elasticity analysis used in many forms of energy modeling. For a more detailed discussion of the results using the translog functional form, see Kobos (2002b).

3. Learning parameter estimates for wind and solar photovoltaic technologies

The following sections outline the procedures and data sources employed in the experience curve analysis for each technology. Results are then compared to the literature and form the basis for scenario analysis. Estimation of the cost curves and resulting learning elasticities was based on the ordinary least-squares method of regression analysis. Data were examined for serial correlation and multicollinearity.

3.1. Wind

Fig. 8 illustrates worldwide cumulative wind energy installations through 2000 from a Sandia National Laboratories wind database.[4] In addition to this installed capacity data, the wind analysis uses the IEA (2002) energy technology RD&D database, EIA (2001) statistics, as well as cost data from a cooperative data set employed by members of the International Institute for Applied Systems Analysis (Miketa and Schrattenholzer, 2004; Criqui, 2000).

The base case assumes a two-factor experience curve with a 5-year time lag and 2.5% annual depreciation factor. Results for the learning by doing and learning by searching rates include a 14.2% decrease in costs for every doubling of installed capacity and an 18.0% decrease in costs for every doubling of RD&D.[5]

Scenarios around the base case include ranging the time lag from 3 to 6 years. A 3–5 year time lag represents the time between the Department of Energy's Advanced Wind Turbine program's initiation in 1990, and their, "goal of developing more competitive machines for the 1993–1995 time period" (Poore, 1997, p. 1). This range is generally accepted among analysts, but may vary widely according to the project-specific nature of the RD&D (Cohen, 2002). For instance, a recent report by the European Wind Energy Association EWEA and Greenpeace International (1999) indicates that European wind research project goals may have a 6-year time lag from RD&D expenditure to commercially viable technology available in the marketplace. Similarly, the depreciation factors can be varied in line with other studies (e.g. Criqui et al., 2000). The annual depreciation factors were varied as 0, 2.5, 5, and 10%, illustrating degrees of 'forgetting' in the RD&D-based knowledge stock variable.

[4]The Sandia National Laboratories (SNL) (2001) wind database is derived from the IEA Wind Energy Annual Report (IEA, various issues) and Windpower Monthly (various issues).

[5]The adjusted R^2 value for the base case was 0.947. The Durbin Watson statistic was 1.324, indicating no serial correlation. The t-statistics for the learning by doing (a_i) and learning by searching (b_i) elasticities presented in Eq. (4) were −5.627 and −1.444, respectively.

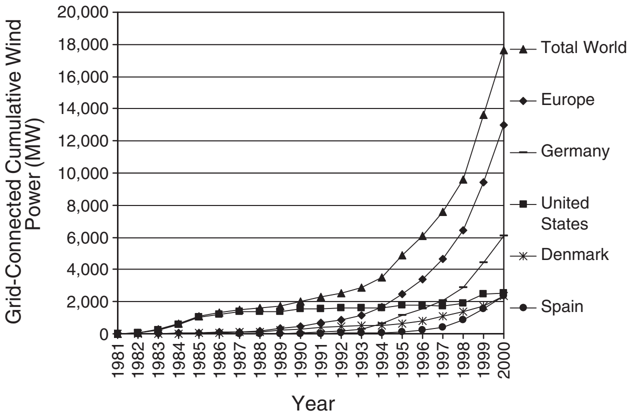

Fig. 8. Worldwide grid-connected cumulative installed MW of wind power (SNL, 2001).

Table 1 summarizes the base case (in bold) and scenario results. Any scenarios that do not meet all the statistical acceptance criteria are highlighted in italics, including criteria for *t*-statistics on parameter estimates, the Durbin Watson (DW) test statistic for serial correlation, and the Variance Inflation Factor (VIF) test for multicollinearity.[6] For perspective, the 0–6-year time lag scenarios' results (including all deprecation rate scenarios) for the learning by doing and learning by searching parameters ranged from 12.3 to 16.8% and 4.9 to 25.7%, respectively. Increasing the depreciation rate from 0 to 0.10 changed the learning by doing and learning by searching percents by 1.4–3.7, and −0.7 to −16.0 percentage points, respectively.

While the time lag and knowledge stock depreciation inputs for the base case scenario were chosen to represent the range of time lag and depreciation inputs considered in Table 1, the resulting learning elasticities are somewhat of an aggressive finding relative to those presented in other studies. For example, Klaassen and Miketa (2002) find that for select European countries, wind energy technology two-factor learning by doing and by searching rates are 5.4% and 12.6%, respectively. Miketa and Schrattenholzer (2004) report wind energy technology two- factor learning by doing and by searching rates of 9.7% and 10%, respectively. Kouvaritakis et al. (2000) illustrate a learning by doing rate of 16% and a learning by searching rate of 7%, whereas Criqui et al. (2000) illustrate similar rates of 16.4% and 4.4%.

3.2. Solar photovoltaics

Capacity data for solar PV technology are most often based on cumulative shipments of cells and modules.[7] For example, the learning rate for the Renewable Energy Technology Characterizations report is based on the capacity (MW) of modules shipped (EPRI and DOE, 1997). Additionally, the data and information compiled in Paul Maycock's data books (2001a, b), his PV News publication, and previous work (Maycock and Wakefield, 1975) are used in many other solar PV cost, learning, and experience curve studies including Chapman and Erickson (1995), Gee and Ciszek (1996), Harmon (2000), Hammond and Turpin (1997), Flavin and O'Meara (1998), Brown (2000), Ricaud (2000), Handleman (2001) and Witt (2001).

The relative levels of PV cells and modules installed and shipped in the world have increased dramatically over the last few decades. Fig. 9 illustrates the shipment trends in the US, Japan, Europe, and the world cumulative total over the last few decades. Detailed data at the country-level was not available until 1988, as represented by the divergence in Fig. 9.

In regards to cost, the manufacturer's price is often used. The cost proxy data comes from two central reports by Paul Maycock (2001a, b) that assume a constant profit margin in the price data—thereby stabilizing market price swings. To estimate learning by searching, the analysis uses the IEA (2002) energy technology RD&D database and the EIA (2001) statistics at the worldwide level.

Similar to the wind analysis, the data was used to estimate a two-factor experience curve. The base case assumes a 3-year time lag and 10% depreciation factor, assumptions consistent with other analyses (Watanabe et al., 2000; Criqui et al., 2000). Base case results for the learning by doing and learning by searching rates are 18.4% and 14.3%, respectively, summarized in Table 2. The solar PV data exhibited serial correlation, and therefore was adjusted using an autoregressive procedure of the first order and retested with the Lagrange Multiplier (LM) test.

Sensitivity analysis on the time lag assumption ranges from 3 to 5 years based on the 3 year time lag analysis of Watanabe et al. (2000). Depreciation factors were also varied as 0%, 2.5%, 5%, and 10% per year for the full analysis building on the obsolescence rate concept of Watanabe et al. (2000). The results of the sensitivity analysis indicate that only the 3 year, 10% depreciation rate scenario meets all the statistical cutoff criteria.[8] For

[6]Acceptance criteria include scenarios with *t*-statistics for learning by doing and learning by searching parameters greater than the 90% level of significance, $1.255 < DW < 2.745$ (indicating no serial correlation), and VIF $\leqslant 10$ (indicating no strong multicollinearity) (See Kobos, 2002b).

[7]Data reporting the cumulative MW shipped may not distinguish between modules and cells. For the analysis, total MW data is required and so MW represents cells and modules shipped.

[8]The remaining 3-year and all of the 4-year lag scenario results yielded *VIF* values >10, above the general $VIF \leqslant 10$ cutoff criteria for multicollinearity, an indication of strong relationships between

Table 1
Wind energy two-factor experience curve results, 1981–1997[a]

Scenario (time lag, depreciation factor)	Cumulative capacity (*CC*)		Knowledge stock (*KS*)				
	Learning by doing elasticity	*LRD* (%)	Learning by searching elasticity	*LRS* (%)	Adj. R^2	*DW*	*VIF*
(0, 0)	*−0.189 [−3.497]*	*12.3*	*−0.429 [−1.619]*	*25.7*	*0.949*	*1.374*	*11.629*
(3, 0)	−0.202 [−4.251]	13.1	−0.339 [−1.572]	20.9	0.948	1.397	8.929
(3, 0.025)	*−0.202 [−3.856]*	*13.1*	*−0.396 [−1.411]*	*24.0*	*0.947*	*1.365*	*10.537*
(3, 0.05)	*−0.211 [−3.709]*	*13.6*	*−0.409 [−1.127]*	*24.7*	*0.944*	*1.297*	*11.865*
(3, 0.10)	*−0.265 [−5.381]*	*16.8*	*−0.073 [−0.165]*	*4.9*	*0.939*	*1.144*	*8.155*
(4, 0)	−0.211 [−4.945]	13.6	−0.294 [−1.553]	18.4	0.948	1.377	7.169
(4, 0.025)	−0.214 [−4.768]	13.8	−0.326 [−1.403]	20.2	0.947	1.344	7.702
(4, 0.05)	*−0.222 [−4.803]*	*14.3*	*−0.331 [−1.183]*	*20.5*	*0.945*	*1.291*	*7.857*
(4, 0.10)	*−0.253 [−6.123]*	*16.1*	*−0.180 [−0.523]*	*11.7*	*0.940*	*1.172*	*5.838*
(5, 0)	−0.218 [−5.624]	14.0	−0.263 [−1.556]	16.7	0.948	1.355	5.898
(5, 0.025)	**−0.221 [−5.627]**	**14.2**	**−0.286 [−1.444]**	**18.0**	**0.947**	**1.324**	**5.943**
(5, 0.05)	*−0.227 [−5.810]*	*14.6*	*−0.291 [−1.273]*	*18.3*	*0.946*	*1.282*	*5.733*
(5, 0.10)	*−0.247 [−7.028]*	*15.7*	*−0.228 [−0.836]*	*14.6*	*0.942*	*1.191*	*4.346*
(6, 0)	*−0.224 [−6.270]*	*14.4*	*−0.235 [−1.520]*	*15.0*	*0.948*	*1.338*	*4.991*
(6, 0.025)	*−0.228 [−6.432]*	*14.6*	*−0.249 [−1.418]*	*15.9*	*0.947*	*1.309*	*4.818*
(6, 0.05)	*−0.233 [−6.757]*	*14.9*	*−0.253 [−1.291]*	*16.1*	*0.946*	*1.276*	*4.478*
(6, 0.10)	*−0.247 [−7.996]*	*15.7*	*−0.223[−0.994]*	*14.3*	*0.943*	*1.206*	*3.422*

[a]Base case result in **bold**. *T*-statistics in [brackets]. Scenarios not meeting all statistical acceptance criteria in *italics*. The learning rate for learning by doing (*LRD*) and the learning rate for learning by searching (*LRS*) are calculated using Eq. (3), and the elasticities from Eq. (4).

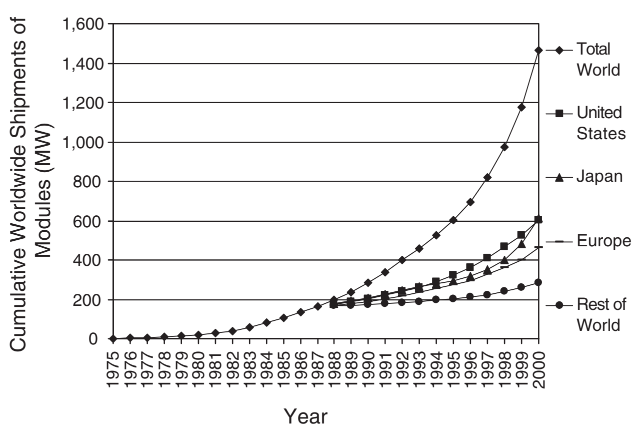

Fig. 9. Worldwide cumulative shipments of PV modules (Maycock, 2001a, b).

perspective, the 0–4-year time lag scenario results (including all deprecation rate scenarios) for the learning by doing and learning by searching parameters ranged from 11.4 to 18.4% and 12.9 to 25.9%, respectively. Increasing the depreciation rate from 0 to 0.10 changed the learning by doing and learning by searching percents by –0.2 to 5.6, and –2.0 to –4.0 percentage points, respectively. The 5-year scenario results had a negative (and theoretically incorrect) sign on the learning by doing parameters.

The scenario results are in line with results presented in other studies. For example, Kouvaritakis et al. (2000) find solar PV energy technology two-factor experience curve learning by doing and by searching rates of 25% and 10%, respectively. Miketa and Schrattenholzer (2004) report solar PV two-factor learning by doing and by searching rates of 17.5% and 10%, respectively. Criqui et al. (2000) illustrate two pairs of estimates, including learning by doing and by searching rates of 16.6% and 36.0%, and 25.0% and 9.0%. Klaassen et al. (2001) illustrate similar learning by doing and by searching rates of 17.5% and 10%, respectively.

4. Implications for cost modeling and policy planning

Incorporating learning effects for cumulative capacity (learning by doing) and RD&D (learning by searching) in a two-factor experience curve provides a statistically robust and transparent approach to capital cost projections for wind and solar PV technologies. The results reinforce themes in the institutional economics literature on the importance of RD&D investment and learning networks early in a technology's evolution and market fruition. Sustained investment is particularly critical against a backdrop of economic, cultural, and political path dependence of traditional fuels and energy

(*footnote continued*)
independent variables and thus high variance of the parameter estimates. The 0-year scenario result has an $L.M. > 6.635$, indicating serial correlation. All of the 5-year scenario results yielded *t*-statistics <1, below the 90% significance cutoff criteria (See Kobos, 2002b).

Table 2
Solar PV energy two-factor experience curve results, 1975–2000[a]

Scenario (time lag, depreciation factor)	Cumulative capacity (*CC*)		Knowledge Stock (*KS*)				
	Learning by doing elasticity	*LRD* (%)	Learning by searching elasticity	*LRS* (%)	Adj. R^2	*LM*	*VIF*
(0, 0)	*−0.254 [−3.036]*	*16.1*	*−0.433 [−2.057]*	*25.9*	*0.989*	*7.748*	*9.384*
(3, 0)	*−0.202 [−2.340]*	*13.1*	*−0.290 [−2.543]*	*18.2*	*0.991*	*5.293*	*21.508*
(3, 0.025)	*−0.232 [−3.048]*	*14.9*	*−0.269 [−2.599]*	*17.0*	*0.990*	*5.310*	*16.579*
(3, 0.05)	*−0.257 [−3.739]*	*16.3*	*−0.252 [−2.632]*	*16.0*	*0.990*	*5.308*	*13.190*
(3, 0.10)	**−0.294 [−4.945]**	**18.4**	**−0.223 [−2.602]**	**14.3**	**0.990**	**5.177**	**9.073**
(4, 0)	*−0.174 [−1.676]*	*11.4*	*−0.267 [−1.997]*	*16.9*	*0.990*	*3.754*	*24.303*
(4, 0.025)	*−0.206 [−2.229]*	*13.3*	*−0.246 [−2.031]*	*15.7*	*0.990*	*3.770*	*19.209*
(4, 0.05)	*−0.231 [−2.765]*	*14.8*	*−0.228 [−2.053]*	*14.6*	*0.990*	*3.804*	*15.525*
(4, 0.10)	*−0.269 [−3.694]*	*17.0*	*−0.200 [−2.052]*	*12.9*	*0.990*	*3.819*	*10.864*
(5, 0)	*0.215 [0.825]*	*−16.1*	*−0.098 [−0.867]*	*6.6*	*0.991*	*1.683*	*22.452*
(5, 0.025)	*0.216 [0.823]*	*−16.2*	*−0.089 [−0.842]*	*6.0*	*0.991*	*1.704*	*18.665*
(5, 0.05)	*0.217 [0.823]*	*−16.2*	*−0.081 [−0.823]*	*5.5*	*0.991*	*1.719*	*15.679*
(5, 0.10)	*0.218 [0.824]*	*−16.3*	*−0.067 [−0.796]*	*4.5*	*0.991*	*1.738*	*11.514*

[a]Base case result in **bold**. *T*-statistics in [brackets]. Scenarios not meeting all statistical acceptance criteria in *italics*. Accordingly, only the scenario (3, 0.10) meets all the statistical criteria. The learning rate for learning by doing (*LRD*) and the learning rate for learning by searching (*LRS*) are calculated using Eq. (3), and the elasticities from Eq. (4).

technologies. This work also reinforced the impetus to include technological learning in the National Energy Modeling System (NEMS). These models have been criticized for their economic assumptions and moderate to pessimistic technological development representation of renewable energy technologies. However, beginning with the 1993 version of the Annual Energy Outlook based on the NEMS model, and expanding into other energy sector models more recently, these models have sought to include more technological progress (Kydes, 2002).

To translate these findings into policy relevant conclusions, the base case estimates of learning parameters for wind and solar PV highlighted in Tables 1 and 2 provide a basis for illustrative capital cost projections and estimates of years until cost competitiveness with dominant energy technologies. Fig. 10 compares three projections for wind energy against two illustrative target levels for competitiveness both with and without a tax credit at 3.0 and 4.5 cents/kWh, respectively. Levelized energy cost estimates are based on Drennen et al. (2003) assuming: (1) a 20-year average system lifetime; (2) a 10% annual rate of discount; (3) \$976/kW in initial capital costs; (4) 1.1 cents/kWh in operation and maintenance costs; and (5) 2532 h of annual operation (28.9% capacity factor times a maximum 8760 h in a year).

In all three scenarios, the global installed cumulative capacity is assumed to grow from 17,696 MW in 2000 (based on IEA, 2001) to 188,000 MW in 2020 (based on Neij, 1997), with base case learning by doing and by searching rates of 14.2% and 18.0%, respectively. The different projections are based on three RD&D growth

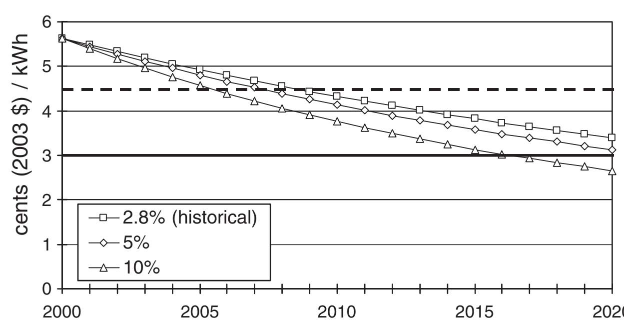

Fig. 10. Projected world average wind energy technology levelized energy cost, annual RD&D growth rate varied.

rates, each starting at a world cumulative RD&D in 2000 of 2.7 billion US dollars derived from the IEA (2002) and the EIA (2001), and growing at 2.8% (a historical global average), 5%, or 10% per year. The levelized energy cost for wind energy reaches a target of 4.5 cents/kWh by 2009, 2007, or 2006 depending on the RD&D growth rate. A more difficult hurdle of 3.0 cents/kWh is reached beyond the projection period for two of the three RD&D scenarios.[9] Subsidies for renewable energy could help close this gap or more on the basis of health and environmental considerations alone (not including a premium for greater energy independence). For example, Jacobson and Masters (2001) present the argument that while energy costs from coal may be 3.5–4 cents/kWh, including health and environmental

[9]Wind energy is competing in many regions of the world that have favorable wind conditions, lower costs, and other factors.

costs brings the energy costs to 5.5–8.3 cents/kWh, easily making wind energy competitive.

Similar scenario analysis can be conducted by varying cumulative capacity, learning by doing and searching rates, the capacity factor, discount rate, system lifetime, and other system costs (i.e. balance of system and maintenance costs). A similar analysis of solar PV, solar thermal, and geothermal cost projections are reported in Kobos (2002b). While estimates of time to cost competitiveness vary (with wind being quite favorable), all analyses point to a strong role for a coordinated RD&D national policy.

5. Summary and conclusions

Given the estimates of learning effects and cost scenarios presented in this article, a return to 1970s-era goals for a US system of renewable technology innovation could greatly accelerate market penetration. Each of four technologies (wind, solar photovoltaic, concentrated solar power, and geothermal) received substantial financial and institutional support shortly after the energy crises in the 1970s. Since that time, however, not one of these four technologies maintains a true national system of innovation.

For example, although wind technology costs have recently declined in real terms, the US system of innovation has been too fragmented to account for recent reductions. Rather, recent growth in US wind energy installations is more a result of financial incentives for installation and capital cost reductions from abroad than for technology innovation in the domestic wind industry. RD&D collaborations between US-based actors and foreign colleagues only serve to promote the use of wind power and therefore the domestic wind industry. These developments lend evidence to the argument that capital cost ranges for energy technologies may be international by nature, but progressing from the innovation to market diffusion stage for a technology is still likely dependent on national institutions.

For solar PV, the US has yet to reach its goals of over 20 years ago. During the late 1970s and early 1980s several laboratories including the National Renewable Energy Laboratory and Sandia National Laboratories were given the task to achieve "technology readiness" by 1982 and "commercial readiness" by 1986 according to the PV plan of 1978 (NREL, 2000a, p. 1). However, along with declining real oil prices throughout the 1980s came a decline in political support for renewables. US RD&D funds for solar photovoltaics declined 77% in real terms (2003 $) between 1980 and 2000 (IEA, 2002; BEA, 2004). In more recent years, federal support for PV can be primarily found in US energy laboratories and a select few domestic industry participants. The National Renewable Energy Laboratory, Sandia National Laboratories, the PV Program of the Department of Energy, and participants in the PV industry still maintain and foster some laboratory/industry links for renewable energy technologies. The recent Photovoltaic Program Five-Year Plan and the Photovoltaic Industry Roadmap define the challenges for government and private industry goals (NREL, 2000b; Energetics, 2001).

The potential for a renewed US system of innovation for renewables has not gone unnoticed. During the late 1990s, the declining energy RD&D trend was recognized as a potentially long-term problem for energy security and environmental sustainability. The President's Committee of Advisors on Science and Technology (PCAST) produced three energy studies to address these concerns. Specifically, the reports helped to lay the foundation for broader academic, industrial, and nongovernmental organization involvement in energy RD&D.[10]

Recent increases in international oil prices and concerns about oil supply create a feeling of history repeating itself from the 1970s energy crises. Additionally, the California energy crisis of 2000–2001 highlighted key points between the energy supply, demand, infrastructure, markets, and most importantly, the energy production mix for the US in the new millennium (Faruqui et al., 2001). However, despite these developments and recommendations by PCAST to modestly increase renewable energy RD&D funding above their initial levels by approximately 3% annually between 2001 and 2003,[11] renewable energy RD&D funding requests increased by 1% between 2001 and 2002, and 3% between 2002 and 2003 (DOE, 2004).[12] Without sustained support for renewable energy both at the federal level (through RD&D) and in the commercial marketplace, it is unclear how quickly these energy technologies will continue to penetrate the market.

The methodology outlined in this article is transparent, yet should be considered a preliminary study of learning and innovation through capacity development and RD&D. Future work could examine different formulations of the two-factor learning curve and other methods of analysis (Miketa and Schrattenholzer, 2004). This work would increase the level of fidelity for RD&D's role in more complex energy policy planning models. With this understanding, and the methodologies

[10]The reports included, "The US Program of Fusion Energy Research and Development," July 1995; "Federal Energy Research and Development Challenges of the Twenty-First Century," November 1997; and "Powerful Partnerships: The Federal Role in International Cooperation on Energy Innovation," July 1999 (Holdren and Baldwin, 2001).

[11]PCAST recommendations for federal technology R&D, Renewable column, Table 1 (Holdren and Baldwin, 2001, p. 416).

[12]Excluding hydrogen energy systems from the DOE (2004) figures reveals the funding for renewable energy increased less than 1% between 2001 and 2002, and decreased by 1% between 2002 and 2003.

developed in this article, energy policy makers can gain insight into how energy technology costs may change over time, thereby providing the basis for energy policy planning and analysis.

Acknowledgements

Peter H. Kobos wishes to thank Leo Schrattenholzer of the International Institute for Applied Systems Analysis (IIASA) for initiating this study during the summer of 2000. The authors also thank Arnold B. Baker and an anonymous reviewer for their helpful comments on an earlier draft. We also thank Sandia National Laboratories for their support under Contract 17633.

References

Argote, L., 1999. Organizational Learning: Creating, Retaining and Transferring Knowledge. Kluwer, Dordrecht, Netherlands.

Arrow, K., 1962. The economic implications of learning by doing. Review of Economics Studies 29, 154–174.

Arthur, W.B., 1988. Self-Reinforcing mechanisms in economics. In: Anderson, P.W., Arrow, K.J., Pines, D. (Eds.), The Economy as an Evolving Complex System. Addison-Wesley Publishing Company, Redwood City, CA, pp. 9–31.

Arthur, W.B., 1989. Competing technologies, increasing returns, and lock-in by historical events. The Economic Journal 99, 116–131.

Asmus, P., 2001. Reaping the Wind. Island Press, Washington, DC.

AWEA, 2001. Wind Energy: US Installed Capacity (Megawatts), 1981–1999. American Wind Energy Association. January 24, 2002. http://www.awea.org/faq/instcap.html.

Ayres, C.E., 1957. Institutional economics: discussion. American Economic Review, Papers and Proceedings 47, 26–27.

Barreto, T.L., 2001. Technological learning in energy optimization models and deployment of emerging technologies. Ph.D. thesis. The Swiss Federal Institute of Technology, Zurich, Switzerland.

BEA, 2004. Current-Dollar and "Real" Gross Domestic Product. Bureau of Economic Analysis. August 21, 2004. http://www.bea.gov/bea/dn/home/gdp.htm.

Boston Consulting Group, 1968. Perspectives on Experience. Boston Consulting Group Inc., Boston, MA, USA.

Brown, L., 2000. State of the World 2000. World Watch Institute. W.W. Norton & Company, New York.

BTM Consult ApS, 2004. World Market Update 2003. Ringkøbing, Denmark.

Chapman, D., Erickson, J., 1995. Residential rural solar electricity in developing countries. Contemporary Economic Policy 13, 98–108.

Christiansson, L., 1995. Diffusion and Learning Curves of Renewable Energy Technologies. IR-95-126. IIASA, Laxenburg, Austria.

Cohen, J., 2002. Princeton Energy Research Institute. Rockville, Maryland. Personal communication. May 17.

Cohendet, P., Llerena, P., 1997. Learning, technical change, and public policy: how to create and exploit diversity. In: Edquist, C. (Ed.), Systems of Innovation. Pinter, London, pp. 223–241.

Cory, K.S., Bernow, S., Dougherty, W., Kartha, S., Williams, E., 1999. Analysis of wind turbine costs reductions: the role of research and development and cumulative production. AWEA's Windpower '99 Conference, Burlington, VT, June 22, 1999.

Criqui, P., 2000. Data for the Two-Factor Learning Curve. IEPE, Grenoble, France December 15.

Criqui, P., Klaassen, G., Schrattenholzer, L., 2000. The Efficiency of Energy R&D Expenditures. Economic Modelling of Environmental Policy and Endogenous Technological Change Workshop. Institute for Environmental Studies, Amsterdam November 16–17.

Crossan, M.M., Lane, H.E., White, R.E., 1999. An organizational learning framework: from intuition to institution. Academy of Management Review 24 (3), 522–537.

DOE, 2004. Office of Management, Budget & Evaluation. FY 2003 and FY 2004 Control Table by Appropriation. Department of Energy. August 22, 2004. http://www.mbe.doe.gov/budget/.

Drennen, T.E., Baker, A.B., Kamery, W., 2003. Electricity Generation Cost Simulation Model (GenSim). SAND2002-3376, Sandia National Laboratories, October.

Edquist, C., Johnson, B., 1997. Institutions and organizations in systems of innovation. In: Edquist, C. (Ed.), Systems of Innovation. Pinter, London, pp. 41–63.

EIA, 2001. US department of energy renewable energy research and development appropriations, fiscal years 1978–1999. Table C4. Energy Information Administration. August 27, 2002. http://www.eia.doe.gov/oiaf/servicerpt/subsidy/table_c4.html.

Energetics, 2001. Solar electric power: the US photovoltaic industry roadmap. photovoltaic systems symposium, July 18–20,Albuquerque, NM. August 27, 2002. http://www.nrel.gov/ncpv/pdfs/30150.pdf.

EPRI and DOE, 1997. Renewable energy technology characterizations. Electric Power Research Institute and the US Department of Energy. TR-109496, December.

EWEA and Greenpeace International, 1999. Windforce 10: A Blueprint to Achieve 10% of the World's Electricity from Wind Power by 2020. European Wind Energy Association. February 4, 2002. http://www.greenpeace.org.

Faruqui, A., Chao, H., Niemeyer, V., Platt, J., Stahlkopf, J., 2001. Analyzing California's power crisis. The Energy Journal 22 (4), 29–52.

Flavin, C., O'Meara, M., 1998. Solar Power Markets Boom. World Watch. September/October.

GE, 1977. Wind energy mission analysis. executive summary. Prepared for the United States Energy Research and Development Administration; Division of Solar Energy. General Electric. ERDA Contract No. EY-76-C-02-2578. February.

Gee, J.M., Ciszek, T.F., 1996. The crystalline-silicone photovoltaic R&D project at NREL and SNL. NREL/SNL PV Program Review Meeting, Lakewood, CO. November, 18–22.

Hammond, R.L., Turpin, J.F., 1997. PV Batteries and Charge Controllers: Technical Issues, Costs and Market Trends. Preprint: 26th IEEE PVSC. September 29–October 3.

Handleman, C., 2001. An experience curve based model for the projection of PV module costs and its policy implications. Utility Photovoltaic Experience Conference & Exhibition 2001, Sacramento, California, USA, October 2–4.

Harmon, C., 2000. Experience Curves of Photovoltaic Technology. IR-00-014. IIASA, Laxenburg, Austria.

Hodgson, G., 1989. Institutional rigidities and economic growth. Cambridge Journal of Economics 13, 79–101.

Holdren, J.P., Baldwin, S.F., 2001. The PCAST energy studies: toward a national consensus on energy research, development and demonstration, and deployment policy. Annual Review of Energy and Environment 26, 391–434.

Horner, J., 1989. The role of technology: an institutional debate. Journal of Economic Issues 23 (2).

IEA, 2001. Wind Energy Annual Report 2000. International Energy Agency. May.

IEA, 2002. IEA Energy Technology R&D Database. International Energy Agency. August 27, 2002. www.iea.org/stat.htm.

IEA, various issues. Wind Energy Annual Report. International Energy Agency.

Jacobson, M.Z., Masters, G.M., 2001. Exploiting wind versus coal. Science 293 August.

Klaassen, G., Miketa, A., 2002. The impact of R&D on innovation for wind energy in Denmark, Germany and the UK. International Energy Workshop, Stanford University, USA, June 18–20.

Klaassen, G., Miketa, A., Riahi, K., Schrattenholzer, L., 2001. Targeting technological progress towards sustainable development. 18th Congress of the World Energy Council. Buenos Aires, Argentina, October 21–25.

Kobos, P., 2002a. Technological learning: the empirics and implications for renewable energy technology. Presentation at the International Energy Workshop, Stanford University, USA, June 18–20.

Kobos, P.H., 2002b. The implications of renewable energy research and development: policy scenario analysis with experience and learning effects. Ph.D. Dissertation, Ecological Economics, Rensselaer Polytechnic Institute, Troy, NY, December.

Kobos, P.H., 2002c. The empirics and implications of technological learning for renewable energy technology cost forecasting. Proceedings of the 22nd Annual North American Conference of the USAEE/IAEE, Vancouver, B.C., Canada, October 6–8.

Kouvaritakis, N., Soria, A., Isoard, S., 2000. Modeling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching. International Journal of Global Energy Issues 14 (1-4), 104–115.

Kydes, A., 2002. Office of integrated analysis and forecasting, energy information administration. Personal communication. February 27.

Li, G., Rajagopalan, S., 1998. A learning curve model with knowledge depreciation. European Journal of Operations Research 105, 143–154.

Lucas Jr., R.E., 1988. On the mechanics of economic development. Journal of Monetary Economics 22, 3–42.

Mankiw, N.G., Romer, D., Weil, D.N., 1992. A contribution to the empirics of economic growth. Quarterly Journal of Economics 107, 407–437.

Margolis, R.M., Kammen, D.M., 1999a. Underinvestment: the energy technology and R&D policy challenge. Science 285.

Margolis, R.M., Kammen, D.M., 1999b. Evidence of under-investment in energy R&D in the United States and the impact of Federal policy. Energy Policy 27 (10), 575–584.

Maycock, P.D., 2001a. Photovoltaic Technology, Performance, and Cost 1995–2010. PV Energy Systems Inc., Warrenton, VA.

Maycock, P.D., 2001b. The World Photovoltaic Market. PV Energy Systems Inc., Warrenton, VA.

Maycock, P.D., Wakefield, G.F., 1975. Business Analysis of Solar Photovoltaic Energy Conversion. Texas Instruments Incorporated, Dallas, TX.

McDonald, A., Schrattenholzer, L., 2001. Learning rates for energy technologies. Energy Policy 29 (4), 255–261.

McVeigh, J., Burtraw, D., Darmstadter, J., Palmer, K., 1999. Winner, loser or innocent victim: has renewable energy performed as expected? Renewable Energy Policy Project (REPP). March 7.

Miketa, A., Schrattenholzer, L., 2004. Experiments with a methodology to model the role of R&D expenditures in energy technology learning processes; first results. Energy Policy 32 (15), 1679–1692.

Mokyr, J., 1990. The Lever of Riches. Oxford University Press, New York, NY.

Muth, J.F., 1986. Search theory and the manufacturing progress function. Management Science 32 (8).

Myrdal, G.K., 1944. An American Dilemma. Harper & Brothers Publishers, New York.

Myrdal, G.K., 1972. Against the Stream. Pantheon Books, New York.

Nakićenović, N., Grübler, A., McDonald, A., 1998. Global Energy Perspectives. Cambridge University Press, Cambridge, UK.

Neij, L., 1997. Use of experience curves to analyze the prospects for diffusion and adoption of renewable energy technology. Energy Policy 25 (13), 1099–1107.

Neij, L., 1999. Cost dynamics of wind power. Energy 24, 375–389.

Nelson, R.R., 1995. Co-evolution of industry structure, technology and supporting Institutions, and the Making of Comparative Advantage. International Journal of the Economics of Business 2 (2), 171–184.

NREL, 2000a. NREL PV working with industry newsletter. National Renewable Energy Laboratory. Second Quarter.

NREL, 2000b. Photovoltaics—energy for the new millennium: the national photovoltaics program plan for 2000–2004. National Renewable Energy Laboratory. August 27, 2002. http://www.nrel.gov/ncpv/pdfs/25847X.pdf.

Poore, R.Z. (PI)., 1997. Advanced wind turbine program near-term prototype testing project. Final Report, Contract AAA-5-15077-01. Prepared for the National Renewable Energy Laboratory, Golden, CO, USA.

Reddy, N.M., Aram, J.D., Lynn, L.J., 1991. The institutional domain of technology diffusion. Journal of Product Innovation Management 8, 295–304.

Ricaud, A., 2000. Comparative impact of publicly funded photovoltaic R&D programmes (USA, Japan, Germany, France, Italy: 1976–1998). Preprint for the 16th EU PVSEC-Glasgow, May, 1–5.

Robertson, M., Swan, J., Newell, S., 1996. The Role of networks in the diffusion of technological innovation. Journal of Management Studies 33 (3), 333–359.

Ruby, D., Gee, J., 2001. History of the crystalline silicone photovoltaic cell research program at Sandia National Laboratories. SAND Report, 2001-0833, April.

Samuels, W.J., 1995. The present state of institutional economics. Cambridge Journal of Economics 19, 569–590.

Schrattenholzer, L., 2000. Procurement and R&D support: two policies aiming at enhancing technical progress. Presentation at the Joint Meeting of the Energy Modeling Forum, the International Energy Agency, and the International Energy Workshop, Stanford University, USA, June 20–22.

Schrattenholzer, L., Kobos, P., 2000. Experiments with different formulations of the 2-Factor learning curve. Presentation at the Systems Analysis for Progress and Innovation in Energy (SAPIENT) meeting. Athens, Greece, September 27–October 1.

Sloth, E., Lundvall, B.A., 1997. National innovation systems and the dynamics of the division of labor. In: Edquist, R. (Ed.), Systems of Innovation. Pinter, London, pp. 242–256.

SNL, 2001. Worldwide Grid-Connected Wind Capacity, Sandia National Laboratories, derived from the IEA Wind Energy Annual Report and Windpower Monthly, various issues, September.

Sonis, M., 1992. Innovation diffusion, schumpeterian competition and dynamic choice: a new synthesis. Journal of Scientific & Industrial Research 51, 172–186.

Union of Concerned Scientists, 1999. A Powerful Opportunity Making Renewable Electricity the Standard. Cambridge, MA.

Venezia, I., 1985. On the statistical origins of the learning curve. European Journal of Operational Research 19, 191–200.

Von Tunzelmann, G.N., 1995. Technology and Industrial Progress. Edward Elgar, Aldershot, UK.

Watanabe, C., 1995a. Mitigating global warming by substituting technology for energy. Energy Policy 23 (4–5), 447–461.

Watanabe, C., 1995b. Identification of the role of renewable energy—A view from Japan's challenge: The New Sunshine Program. Renewable Energy 6.

Watanabe, C., 1999. Systems option for sustainable development—effect and limit of the Ministry of International Trade and Industry's efforts to substitute technology for energy. Research Policy 28, 719–749.

Watanabe, C., 2000. MITI's policy as a system to substitute technology for energy—lessons, Limits and Perspective. The Joint Meeting of the Energy Modeling Forum, International Energy Agency and International Energy Workshop, Stanford University, USA, June 20–22.

Watanabe, C., Wakabayashi, K., Miyazawa, T., 2000. 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. Technovation 20, 299–312.

Watanabe, C., Bing, Z., Griffy-Brown, C., Asgari, B., 2001. Global technology spillover and its impact on industry's R&D strategies. Technovation 21, 281–291.

Wene, C.O., 2000. Experience Curves for Energy Technology Policy. International Energy Agency, OECD, Paris, France.

Windpower Monthly, various issues. Windpower Monthly, A/S, Knebel, Denmark.

Witt, C.E., 2001. Status and recent progress in photovoltaic manufacturing in the USA. NREL/CP-520-29462, Presented at the Sharjah Solar Energy Conference, Sharjah, UAE, February 19−22.

Wright, T.P., 1936. Factors affecting the cost of airplanes. Journal of the Aeronautical Sciences 3.

Zangwill, W.I., Kantor, P.B., 1998. Toward a Theory of Continuous Improvement and the Learning Curve. Management Science 44 (7), 1.