Modeling Technology Learning for Electricity Supply Technologies

Inês L. Azevedo, Carnegie Mellon University, (412) 268-3754, iazevedo@cmu.edu
Paulina Jaramillo, Carnegie Mellon University, (412) 268-6655, paulina@cmu.edu
Ed Rubin, Carnegie Mellon University, rubin@cmu.edu, (412) 268-5897
Sonia Yeh, University of California - Davis, (530) 830-2544, slyeh@ucdavis.edu

Overview

The phenomenon of unit cost reduction associated with increased production (learning-by-doing) has long been documented for manufactured products. In recent decades this has been extended to energy. The most common approach for characterizing this relationship is the use of a log-linear experience curves (or learning curve) relating reductions in the unit cost of a technology to its cumulative production or installed capacity. This model formulation also has become a common method of representing endogenous technical change in energy-economic models used for policy analysis. Yet, there are significant uncertainties in the underlying drivers of technological change, and the "proper" formulation of an experience curve (e.g., the appropriate equation, shape, and parameters of an experience curve). There is uncertainty in how best to use learning curves for making projections and to inform policies.

We review theory of technological change and the underlying drivers for cost reduction reported in the literature. We conducted a comprehensive literature review and a meta-analysis for eleven power generation technologies including fossil-based power plants and renewable electric technologies. We draw lessons and insights potentially applicable to the development and use by energy modelers on how to use learning curves for the following power generation technologies: Pulverized coal (PC) plants with and without carbon capture and sequestration (CCS); Integrated gasification combined cycle (IGCC) plants with and without CCS; Natural gas combined cycle (NGCC) plants with and without CCS; Natural gas-fired combustion turbines; Dedicated biomass plants; Nuclear plants (third-generation); Conventional hydroelectric plants; Geothermal plants; On-shore and off-shore wind turbines; Solar photovoltaic (PV) and concentrating solar thermal plants (CSP). We review the studies in terms of those that used one, two, or multiple factor experience/learning curves.

Methods

There is a large literature that has empirically observed a relationship between unit costs of production and cumulative production across numerous technologies and products. The relationship has been referred to as an "experience curve" or "learning curve" and has been shown to generally take the following generic form [1], which can be represented by $Y = ax^b$, Where Y is the unit cost of production, x is the cumulative experience (which in the energy innovation literature is typically represented by cumulative installed capacity or cumulative energy production) a is the unit production cost of the first unit, and b is a constant capturing the rate of cost reduction.

The *learning rate* (*LR*) is defined as the rate at which the per-unit cost of a technology is expected to decline with every doubling of cumulative production. The factor 2^b is called the *progress ratio*, a parameter also commonly reported in the literature. Numerically it is simply equal to ($1 - LR$). The original derivation of this model form reflected the phenomenon called "learning by doing" (LBD). However, it is often argued that the statistical correlations between a reduction in unit cost and the cumulative installed capacity of an energy technology offers little explanation for the underlying factors and processes of technological change. There is also no inference in the causality between these two variables [2,3,4]. Despite several decades of research, our understanding of the factors that contribute to technological change and cost reductions is still rather limited. Various theories have been proposed to explain observed reductions in unit cost as cumulative output increases. Generally, they fall into three categories: (1) costs fall due to changes in production that include process innovations, worker familiarity in the use of tooling, improved management, and economies of scale; (2) costs fall due to changes in the product itself including product innovations, re-design and standardization; and (3) costs fall due to changes in input prices [5]. Some researchers suggest that the overall learning rates derived from empirical experience curves many over-estimate the actual contribution of true learning-by-doing [2,4], as these models do not account for R&D spending, knowledge spillovers, increased capital investments economies-of-scale, the effect of other public policies, and the effect of changes in input prices. A particular concern is that models that "miss critical pathways or ascribe influence inappropriately could potentially arrive at erroneous, incomplete, or misleading policy conclusions" [4]. These concerns have led to the development of other learning models that incorporate multiple parameters, which we review in our meta-analysis.

Results

We found that there is a wide variation in reported learning rates. Some studies include both learning-by-doing and learning-by-researching (reflecting R&D spending), and report both values. In general, there are wide variations even within the same technologies, and no clear trend of learning rates associated with a certain type of technologies, time periods, or regions. Though we also found a narrower range of smaller learning rates associated with fossil power plants, whereas renewable technologies (wind, solar, biopower) have a wide range of learning rates including values as high as 45% to 53%. With the exception of nuclear power, all the studies we reviewed report cost reductions with increased installed capacity.

Some energy models have experimented with incorporating learning curves and explored the impacts on model results. In general, when one-factor learning curves are adopted, models with endogenous technological learning (ETL) (via learning curves) tend to project higher penetrations of advanced technologies and have lower overall costs compare to models that do not take ETL into account. The conclusions are much more complicated when both learning-by-doing and learning-by-researching (R&D) are included in the model. In general, R&D investments also lead to cost reduction. The results are summarized in Table 1.

Table 1: Summary of studies characterizing historical learning rates for electric power generation technologies.

Technology	Number of studies reviewed	Number of studies with one factor	Number of studies with two factors	Range of learning rates for "learning by doing" (LBD)	Range of rates for "learning by researching" (LBR)	Years covered across all studies
Coal*						
PC	2	2	0	5.6% to 12%		1902-2006
IGCC	1	1	0	2.5% to 7.6%		Projections
Natural Gas*	8	6	2	-11% to 34%	2.38% to 17.7%	1980-1998
Nuclear	4	4	0	<0 to 6%		1975-1993
Wind (on-shore)	35	29	6	-3% to 32%	10% to 26.8%	1980-2010
Solar PV	24	22	2	10% to 53%	10% to 18%	1959-2001
BioPower						
Biomass production	4	4	0	12% to 45%		1971-2006
*Power generation***	7	7	0	0% to 24%		1976-2005
Geothermal power	3	0	0			1980-2005
Hydropower	3	0	2	0.48% to 11.4%	2.63% to 20.6%	1980-2001

**Does not include plants with CCS. **Includes combined heat and power (CHP) and biodigesters.*

Conclusions

The phenomenon of unit cost reduction associated with increased production (learning-by-doing) has long been documented for manufactured products. In recent decades this has been extended to model the cost of various energy supply technologies. Yet, there are significant uncertainties in the underlying drivers of technological change; in our understanding of the major factors that contribute to learning; and in the "proper" formulation of an experience curve (including the appropriate shape and parameters of an experience-based model). Thus, there is uncertainty in how best to use learning curves for making projections and analyzing policy scenarios.

There are two key categories of uncertainties associated with the application of experience curves. One is the learning curve itself; the other concerns the conclusions drawn from the use of learning curves. Despite a rich literature in learning-by-doing and extensive documentation of historical learning for energy technologies, there remains a large degree of uncertainty as to how reliably historical learning curves can be used to estimate the future cost of the same or similar technology. Thus, the judgment of technology experts and modelers is still required and used to address a host of questions, such as: What is the appropriate learning rate? When does learning begin (and end)? What is the appropriate shape of a learning curve? What is the appropriate measure of experience?

The second key uncertainty, regarding the integrity of policy-related conclusions drawn from the use of learning curves, is similarly a topic of discussion and debate. Without a better understanding and ability to model the underlying drivers of technology cost reductions, model projections based on learning rates obtained from one-factor learning curves may inappropriately lend support to policies that favor certain technologies or investment strategies.

Over the longer term, continued research into the underlying factors that govern or influence technological innovations and diffusion may yield improved models that can more reliably forecast the implications of proposed energy and environmental policy measures. In the meanwhile, more concerted efforts are needed to explore, understand and display the consequences of uncertainties in current formulations of technology experience curves used to project the future cost of energy technologies

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