Experience Curves and Solar PV

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Estimation of current and projected future resource costs is a core part of the Western Electricity Coordinating Council's transmission planning for the 10-year Common Case based plan, and even more for the 20-year scenario based plan, both part of the Regional Transmission Expansion Planning (RTEP) project.

The effort to identify current costs is complex and, not surprisingly, the data is neither consistent nor complete. Further, the effort to assess future projected cost is subject to numerous analytical choices.

Both current and future projected costs should be assessed consistently, using the best data available, with transparency on assumptions, methods and the selection of parameters, and balancing all the contributing factors to select the best available estimates given the range of uncertainties involved. While single point estimates may be needed for modeling purposes, it is important to think both present and future resources costs as being ranges rather than fixed values.

It is evident that the question of future solar PV resource costs is a Big Question for the RTEP planning process. While use in the western grid is a very small percentage of all resources at present, there is a strong sense that once solar PV reaches "grid parity"[1] it will rapidly become a much more important part of the mix. Beyond that point, as economics favor rapid uptake, end-use oriented PV will substantially decrease demand, and utility-scale PV will increase supply. And those changes in both sides of the market, along with the unique diurnal and seasonal shape of the solar resource, will significantly affect future grid operations and the need for transmission expansion.

Consequently, the future estimated cost projection for solar PV has been a point of considerable discussion in the RTEP process.

As the development of RTEP modeling has taken shape, there is agreement that the use of a "learning curve" (or "experience curve") method is appropriate for estimating future resource costs.

[1] Recent commentary suggests treating the "grid parity" concept with considerable restraint due to the many and often unspecified assumptions about the context, for example, whether "parity" is based on retail or wholesale power costs, the location, and whether the comparison is based on average or peak pricing (BNEF 2012a: 11). However, "grid parity" remains useful shorthand for the idea that fossil resource prices are generally increasing, and renewable energy is generally decreasing, and at some point the historical advantage fossil based electricity has had will reverse, with significant consequences for future resource mix and transmission deployment.

However, it has been proposed that the experience curve for solar PV should be dramatically changed "downward" going forward (i.e., significantly less of a cost decrease per unit of marginal production).

This short paper will review the background of the experience curve method and the application of that approach to solar PV. We conclude:

(1) The strong preponderance of evidence suggests staying with the consensus experience curve estimate – a Learning Rate of 20% for solar PV modules and 17% for balance-of-system, going forward through the 20-year planning horizon.

(2) Differing levels of future solar PV market expansion should be captured in the different RTEP 20-year scenarios. While the experience curve should be kept constant, there will be different doubling periods for solar PV under differing policy and market conditions.

1. Comparative Analysis of Future Technology Market Penetration and Cost

Numerous approaches have been tried over time to project changes in market penetration, price and time for technology-oriented products (Junginger 2006). Among them are:

- cost per cumulative production
    - learning curves (per firm)
    - experience curves (per industry)
- cost per annum
- cost per annual production
- expert elicitation ("Delphi process")
- engineering models

Observation over many years and new formal analysis suggests that experience curves have the best track record for projecting future costs. A recent paper sponsored by the Santa Fe Institute (Nagy et al. 2012) summarizes a meta-evaluation of estimation methods including cost per cumulative production ("Wright's Law"), cost per annum ("Moore's Law"), cost per rate of annual production ("Goddard's Law"); time-lagged variants of the single factor approaches; and hybrid or multifactor estimators combining the single factor approaches (based on work by Nordhaus and Sinclair, Klepper, and Cohen).

Forecast skill for each of the methods was assessed with a hindcasting approach across 62 technologies in four categories (chemical, hardware, energy and other), with time series ranging from 11 to 39 years.

The analysis concludes that the traditional experience curve approach (Wright) performs quite well across technologies and different time scales, and is significantly better overall than the other approaches, although Moore is very close over shorter time ranges. The robustness of the results for the experience curve approach is striking.

2. Learning Curves and Experience Curves

In 1936, Theodore Wright presented observations of a regularity in cost reduction as planes were manufactured at Boeing. Further studies in industrial manufacturing found similar "learning effects" and became known as the "learning curve," usually expressed as a constant cost reduction per doubling in cumulative production.

The effect is usually expressed as the "learning rate" (LR) or percentage reduction per doubling in cumulative production, or the "progress ratio" (PR), which is reduction relative to the previous period. These are identities; a 20% LR is the same as 80% PR. Both LR and PR parameters continue to be used in the literature.

In the 1960s, especially with influential studies by the Boston Consulting Group, the learning curve concept was expanded from assessment of single-firm product learning curves to industry-wide assessments, and the term "experience curves" came into use. While the terms are still used somewhat interchangeably, because we are looking at global product categories it is more appropriate to use the term "experience curve" in the context of RTEP planning.

3. Characteristics of Experience Curves

Experience curves have been extensively studied and critiqued. Dozens of studies of existing experience curves and meta-analysis across products were reviewed for this paper, showing very consistent results.

Over several decades of use, experience curves have shown regularity across industries and products. When used in an appropriate context, this approach can be a powerful tool for analysis. However, several observations should be made on the range and limitations of the technique.

Observational not functional. While very regular and robust in its results, the experience curve method does not have a clear functional underpinning. Various hypotheses have been proposed for the regularity of the experience curve results as an emergent property of learning, scale economies, development stages, market structure, etc. Conceptually it seems likely all of these are factors that derive broadly from the dynamics of technology diffusion in a market-based economy. Interestingly, the Santa Fe Institute group suggests their analysis shows that scale economies are responsibly for the majority of the effect, with learning a minority but still important component (Nagy et al. 2012: 5).

Scale-free, stable and product-specific. Learning and experience curves show a scale-free but product-specific characteristic value. That is, there is no evidence that, once established, an experience curve deviates much over time throughout a product's history, including end-of-cycle. Since the last doubling, by definition, is half the ultimate market penetration, the effect may appear to be diminished but the constant cost reduction may be spread over a considerably longer time period.

Stability over life cycle, deviations over short spans. Over the typical multi-decadal life cycle of technology-oriented products, the experience curve tends to be quite stable. Overall, experience curves remain constant regardless of developmental stage. However, short-term deviations are often observed at annual or sub-decadal scale, but these appear to be driven by market, production and policy intervention factors as products move from stage to stage -- for example, from innovators to early adopters (Yeh et al. 2007).

Industry analysis generally suggests an "S-curve" approach to technology adoption over time: starting slowly, then rapid uptake, then declining use toward obsolescence (Junginger 2006).

In general, there are two main approaches to development stage analysis, production-based and market-based. Production-based analysis often uses a 6-stage model (e.g., invention, RD&D, niche market, pervasive diffusion, saturation, and senescence). The well-known market-based approach generally has a 5-stage model (innovators, early adopters, middle market, laggards, termination).

While short term changes in experience curves appear within and across developmental stages, especially the early ones, a notable feature of experience curves is regression toward an underlying characteristic Learning Rate/Progress Ratio over longer time scales.

Because of observed short-run variations, some analysts recommend a blended approach of experience curves and expert assessment, especially for shorter-run projections (Black & Veatch 2012). Nevertheless, experience curves provide significant assurance over the longer term.

4. Constraints for Experience Curve Analysis

Effective use of experience curves requires attention to several issues:

Unit of analysis. Selection of the most appropriate production unit is important. When in a "learning curve" context, usually applied to a specific product from a single firm or closely-comparable products across an industry, production counts may be sufficient. But for many products, especially energy technologies, cumulative output capacity is a more relevant measure (IPCC 2011: 366). The selection of the best parameter is still an issue, however.

Over the last several years, for example, the experience curve for wind turbines seemed to deviate well away from the historical record, as turbine prices actually increased for a couple of years. However, this was based on assessment of kW capacity rather than average output or LCOE, both of which improved relative to kW capacity based on increasing blade lengths, sweep areas and hub heights, and improved efficiency for larger turbines (NREL 2012). While the cost based on output or LCOE did deviate somewhat from the historical curve, it did not change sharply and appears to be reverting to the longer-term norm as short-term market factors (for example, rapid run-up in steel prices) work back toward the mean.

Cost comparability. It is important to take an appropriate and consistent approach to converting nominal costs to real costs to preserve comparability across time.

Currency cost normalization. For global experience curves, normalizing cost data through appropriate exchange rate conversions is a key step.

Sub-product experience curves. Observation sometimes indicates that it is appropriate to disaggregate product experience curves. For example, it has long been considered appropriate to have separate solar PV and balance of system (BOS) experience curves, and to consider utility-scale and end-user systems separately (IRENA 2012).

5. Best Uses of Experience Curves

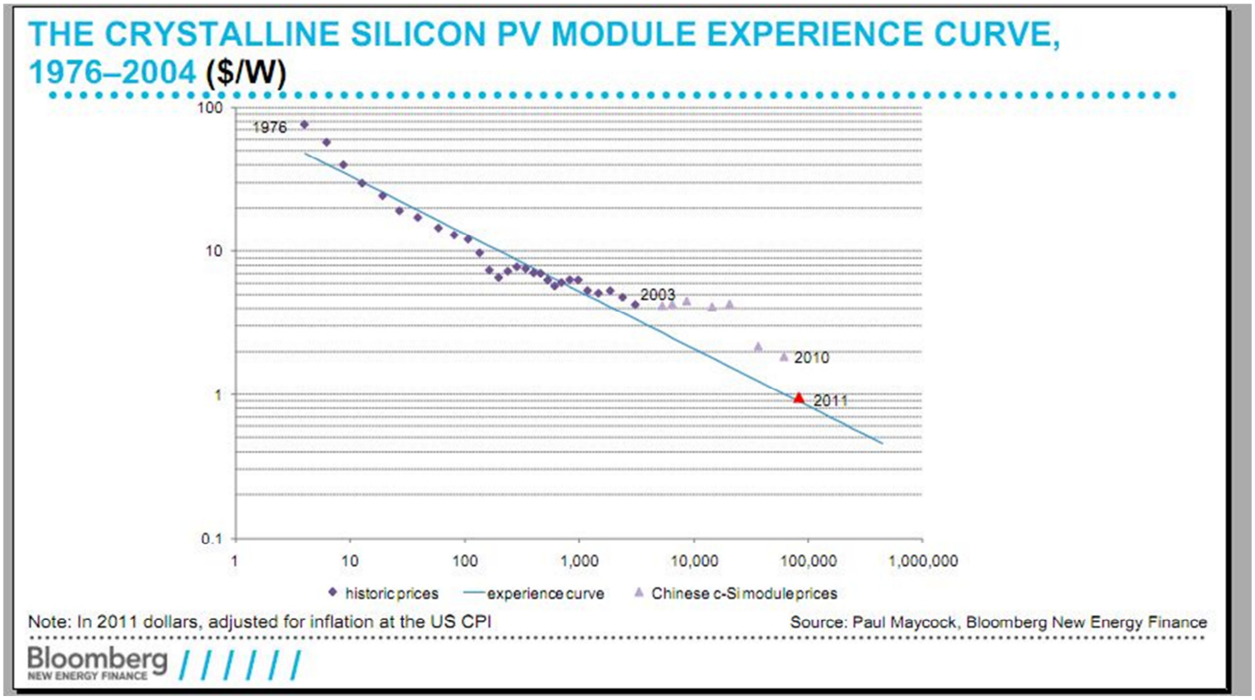
The basic characteristics of experience curves suggest that over time, cost is invariantly related to market size. This turns the standard planning perspective on its head. We usually inquire: what will the market size be assuming a given cost in some future year, using expert judgment, bottom-up engineering and economic modeling to estimate a fixed-point cost. This is the approach most suited to conventional deterministic modeling.

However, the experience curve approach flips this around. The question then is: how large will the market be for a resource in a future year, and then that tells us the cost based on cumulative production. This approach is well suited to dynamical or scenario-based modeling, including the ability to build in varying types and levels of policy interventions and market changes that characterize different scenarios. In this context, experience curves provide a useful exploratory tool.

6. Experience Curves for Solar PV

Experience curves have been an established part of public policy and industry analysis of solar PV and other renewable energy technologies for over three decades. An early study by SERI (1980) laid out a framework approach to learning and experience curves. Numerous projections and refinements using experience curves have been conducted ever since.

While values in published solar PV experience curves range somewhat, with learning rates of 10% to 30%, by far the most common long-term experience curve value for solar PV is 20% (i.e., a 20% cost reduction per doubling of cumulative output). This central tendency persists despite the use of different time periods, different geographic ranges (global or national), and differences in data treatment and analysis.



BNEF 2012b, slide 5

A typical widely-cited analysis by Strategies Unlimited indicates a PR of 80.0% +/- 0.4 (LR = 20%) for 1976-2001. More recently, Nagy et al. (2012) using two slightly different data sets, estimate PR of 81% (LR = 19%) for 1976-2002 or PR of 71% (LR = 29%) for 1977-2009, indicating some sensitivity to late-decade effects. The IPCC's global renewable energy assessment, citing numerous sources, assesses solar PV module learning rate as 20% and balance-of-system between 18% and 21% (IPCC 2012: 380).

7. Can Policy Affect Experience Curves?

Visual examination of experience curves for solar PV and other energy products indicates that policy interventions can affect experience curves temporarily. The well-known pause in PV module cost reductions of the mid-2000s is widely understood as a consequence of feed-in-tariff policies, especially in Germany and Spain. However, this was also accompanied by a dramatic market expansion, decreasing the time span for cumulative doubling. As a result of several factors, including rapid reduction of the Spanish FIT and gearing up global production capacity, module prices have fallen dramatically since 2008, pulling costs back toward the long-term experience curve.

The Santa Fe Institute study (Nagy et al. 2012) also lends credence to the idea that policy intervention either to subsidize cost reductions directly or to expand markets probably has only a temporary effect. They conclude that "Wright's Law" (experience curves) persists across time and products, even though varying policy interventions have occurred across technology sectors.

Another factor to consider is how local costs vary from global levels. For example, at present US solar PV costs are considerably above those in Germany and globally on average. One study concludes, "Lower average installed costs in Germany suggest that deeper near-term cost reductions in United States are, in fact, possible and may accompany increased market scale. It is also evident, however, that market size alone is insufficient to fully capture potential near-term cost reductions, as suggested by the fact that the lowest-cost state markets in the United States are relatively small PV markets. Targeted policies aimed at specific cost barriers (for example, permitting and interconnection costs), in concert with basic and applied research and development, may therefore be required in order to sustain the pace of installed cost reductions on a long-term basis." (LBNL 2012: 43)

In conclusion, an important part of the RTEP scenario building process will be to assess how policy and market drivers may affect the doubling rate of solar PV over the next two decades. But the experience curves themselves should continue as before.

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