Energy Policy 106 (2017) 427–435

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

# Wind power costs expected to decrease due to technological progress

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ARTICLE INFO

*Keywords:*
Wind energy
Technological progress
Cost trends
Forecasting
Energy policy

ABSTRACT

The potential for future cost reductions in wind power affects adoption and support policies. Prior analyses of cost reductions give inconsistent results. The learning rate, or fractional cost reduction per doubling of production, ranges from −3% to +33% depending on the study. This lack of consensus has, we believe, contributed to high variability in forecasts of future costs of wind power. We find that learning rate can be very sensitive to the starting and ending years of datasets and the geographical scope of the study. Based on a single factor experience curve that accounts for capacity factor gains, wind quality decline, and exogenous shifts in capital costs, we develop an improved model with reduced temporal variability. Using a global adoption model, the wind-learning rate is between 7.7% and 11%, with a preferred estimate of 9.8%. Using global scenarios for future wind deployment, this learning rate range implies that the cost of wind power will decline from 5.5 cents/kWh in 2015 to 4.1–4.5 cents/kWh in 2030, lower than a number of other forecasts. If attained, wind power may be the cheapest form of new electricity generation by 2030, suggesting that support and investment in wind should be maintained or expanded.

## 1. Background

The declining costs of solar photovoltaics is a well-known phenomenon used in advocating for continued government support for the technology. Past and future cost reductions for wind power, in contrast, are under more contention. In 2015, wind produced 8 times as much energy as solar at 60% of the cost, putting it close to price parity with traditional technologies (EIA 2009; EIA 2016b; Wiser and Bolinger, 2015). Since the turn of the century, the wind industry has experienced rapid growth and improving economic competitiveness (Wiser and Bolinger, 2015). However, over this time, stagnating capital costs have raised concerns that wind has matured and further investments will not yield significant cost reductions (Bolinger and Wiser, 2011).

In this work we forecast wind power cost, developing empirical models that reproduce historical cost trends. Forecasting cost reductions due to technological progress is usually done through experience curves and learning rates. The experience curve is the observed power law decline in a characteristic relative to the cumulated experience of that characteristic's process (Wright, 1936; Arrow, 1962). In energy economics, the single factor experience curve takes the form:

$$C = C_0(P/P_0)^{-\alpha} \tag{1}$$

where C is price per unit, P is the units produced, $C_0$ and $P_0$ are initial cost and production values, and α is the learning coefficient. The learning coefficient α is used to find the cost reduction for each doubling of cumulative output, also called the learning rate (LR). LR is specified by the equation:

$$LR = 1-2^{-\alpha} \tag{2}$$

Originally, the learning rate was used to identify cost reductions from increasing experience in an airplane manufacturing plant (Wright, 1936). Since this early work, the learning rate has been used to explain cost reductions for a wide variety of technologies. While generalizations of Eq. (1) that include two or more factors have been developed, the single factor learning curve measures aggregate progress with fewer input parameters, e.g. research and development investments. Despite its simplicity, the single factor experience curve Eq. (1) fits empirical data surprisingly well. Nagy et al. (2013) showed that R-squared exceeds 90% for a majority of 62 investigated technologies.

Recent reviews of the energy experience curve literature found large variations in the range of reported learning rates (Lindman and Söderholm, 2012; Rubin et al., 2015). The range of learning rate estimates for wind power was particularly high, ranging from −3% to 33% (Rubin et al., 2015). A negative learning rate implies that wind power is getting more expensive over time, while a 33% learning rate denotes extremely rapid declines in wind electricity cost as more is produced. Fig. 1 illustrates the combined results of two meta-analyses

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http://dx.doi.org/10.1016/j.enpol.2017.03.032
Received 11 September 2015; Received in revised form 8 March 2017; Accepted 13 March 2017
Available online 12 April 2017

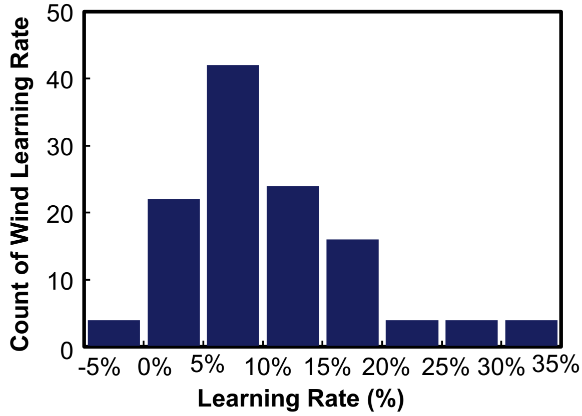


**Fig. 1. Wind Learning Rate Literature Summary**. The count is the number of occurrences of a learning rate in the wind literature. 120 learning rates estimated in 41 publications are reported, gathered from two meta-analyses (Lindman and Söderholm, 2012; Rubin et al., 2015). As explored further in this paper, this wide variation arises from differences in start and end dates, which country's data are used, and what type of model is used. The dates range from 1980 to 2010, with many focusing on the 1990–2000 period. Countries studied include Denmark, Germany, Spain, UK, and the US, with some aggregating to a global scale via some combination of these countries. The most common model used is a single-factor experience curve focusing on capital cost and installed capacity, but multifactor models, production, and levelized cost of electricity are also represented.

for wind learning rates and highlights the lack of consensus from 120 different analyses. This lack of consensus could convince some that the learning rate approach is not suitable for wind power.

Summarizing prior work on retrospective modeling of wind costs, a 2000 report from the International Energy Agency reviewed the then-current state of wind experience curves (e.g. Neij, 1999) and included new estimates (IEA, 2000). A wide variety of wind learning rates are reported, from 4% for Denmark (1982–1997), to 18% in the European Union (1980–1995), to 32% in the US (1984–1994), though the reasons for these stark differences were not explained. Using capital cost ($/W) as the dependent variable, the Wind Technology Market Report series has learning rate results for different time periods, e.g. 8.3% for 1982–2010 and 14.4% for 1982–2004 (Wiser and Bolinger, 2015). There are many additional studies for different regions and time periods, e.g. (McDonald and Schrattenholzer, 2001; Ibenholt, 2002; Junginger et al., 2009). There are also multi-factor learning curve studies separating cost reductions into learning-by-doing and learning-by-research (Miketa and Schrattenholzer, 2004; Klaassen et al., 2005; Jamasb and Köhler, 2007; Söderholm and Sundqvist, 2007; Ek and Söderholm, 2010). Learning-by-doing rates vary from 1% to 17%, learning-by-research varies from 5% to 27%. Most prior analyses use capital cost ($/kW) as the dependent variable. A notable exception is (Neij et al., 2003), who found differences in learning rate using capital cost ($/kW) versus Levelized Cost of Electricity (LCOE) ($/kWh) measures.

Forecasting wind power costs draws from a number of approaches, including experience curves, engineering models, expert elicitation and scenario analysis. (Lantz et al., 2012) synthesized outcomes of 18 scenarios from different regions for wind cost reductions. Results ranged from 0% to 40% reduction to 2030, with a 20–30% reduction in cost representing the 20th to 80th percentiles of the scenarios. Part of our goal is to compare our analytical results with governmental expectations for reductions in wind cost. Focusing on the United States, the primary articulation of governmental understanding of energy systems is the Annual Energy Outlook (AEO) from the Energy Information Administration (EIA, 2014). AEO forecasts are powered the by National Energy Modeling System (NEMS), a techno-economic model of the U.S. energy system with interacting modules describing supply and demand for electricity, fossil and bio-fuels (EIA, 2016a). The forecasting perspective for wind is summarized in this excerpt from *Assumptions to the AEO 2015*: "Capital costs for wind technologies are assumed to increase in response to: (1) declining natural resource quality … (2) increasing costs of upgrading existing local and network …, and (3) market conditions, such as the increasing costs of alternative land uses…" (EIA, 2015a). Results are consistent with this perspective: AOE 2015 forecasts the LCOE of wind to be $73.6/MWh in 2020, increasing to $75.1/MWh in 2040 (both in 2013 US$) (EIA, 2015b).

A different section of the U.S. DOE, the Wind and Water Power Technologies Office, has sponsored the Wind Technology Market Report series since 2008 (Wiser and Bolinger, 2015 and earlier) and recently, a Wind Vision study (DOE, 2015). The Wind Vision study considers technological progress, geographical distribution of wind resources, and economic background factors to build a scenario of wind adoption in the U.S. From the results, learning rates for onshore wind can be inferred as 6% in the base case, with 0% and 11% for pessimistic and optimistic cases respectively. In summary, the main energy model informing the U.S. government forecasts small increases in wind cost and the wind specialists within DOE forecast modest decreases. This review of the U.S. situation underscores pervasive and important questions for energy policy: What expectations do governments have for technological progress? How were these expectations developed? How do they affect energy policy decisions?

Despite a long history of research on the wind experience curve and cost forecasting, there is still a need to better understand the disagreement and improve the empirical basis for model choice. We investigate three issues central to the wind experience curve: temporal "stochasticity", geographical boundaries and model structure.

*Temporal "stochasticity"* refers to variability in model results with different start and end years for data-sets. The ideal start year of a technological progress model for wind power depends on the particular institutional context in the region of interest. While analysts strive to gather as much data as possible, it is generally impractical to retroactively gather data for wind projects built decades in the past. The end year of a data-set depends on when a study is done, typically a year or two prior to the analysis.

As analysts generally have little control over the earlier start and latest end-years of data sets, we treat these as variables and explore how learning rate results changes as a function of different temporal bounding within the available data.

*Geographical boundaries* refer to choices in regional aggregations used in modeling. Many prior studies have analyzed wind power trends at the national level, e.g. for China (Qiu and Anadon, 2012), the U.S. (IEA, 2000) and even a national sub-region (California) (McDonald and Schrattenholzer, 2001)). There have also been global studies (e.g. Junginger et al., 2005, 2009), though data limitations have led to national prices used as proxies for global values.

A national experience curve model would be appropriate if wind technology were separately developed within each nation. While portions of the cost of a wind farm are more local in nature, e.g. construction, the wind industry is a highly globalized one, with multinational firms dominating production (Navigant, 2015). Some future experience curve model, enabled by as yet unavailable data, might succeed in resolving how different cost components fall according to different scales of geographical activity. However, given current data availability, the global nature of the wind industry suggests that a global experience curve is the most appropriate choice.

A global experience curve has the following form:

$$C(GP) = C_0(GP/GP_0)^{-\alpha_g} = C_0\left(\sum P^j / \sum P_o^j\right)^{-\alpha_g} \tag{3}$$

where the global cumulative production of wind power, GP, can also be expressed as a sum over cumulative production $P^j$ in j nations, and $\alpha_g$ is a global learning rate. Ideally, $C_0$ is global average cost, but lack of a consistent global dataset implies that national values need to be used as a proxy.