CHAPTER 6

Onshore wind energy

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Abstract

Onshore wind has shown cost reductions for more than three decades, but the importance of underlying factors has varied over time. While in the past the cost of capacity was mainly used to measure cost reductions, this chapter analyzes the reduction of the levelized cost of electricity (LCOE). Next to lower upfront capital expenditures (Capex), the capacity factor has also increased significantly, going hand in hand with higher hub heights and larger rotor diameters. While Capex and LCOE have also temporarily increased between 2005 and 2011, the overall learning rate for LCOE for data between 1990 and 2017 is 11.4%. Combining this learning rate with anticipated growth in global onshore wind deployment yields a projected LCOE of 3.7$ cents/kWh by 2030, a reduction of approximately 25% from 2018 levels, making it highly competitive with expected prices of new coal and natural gas generation. A recent expert elicitation study of future costs of wind power yielded a range of implicit future learning rates between 14% and 18%. The 11.4% learning rate estimated here yields less bullish prospects for cost reductions; this distinction can be partly explained by the fact that there are a few factors still excluded or partially excluded from the learning-rate analysis (specifically, improvements in project lifetime, operational expenditures, and financing costs).

Chapter outline

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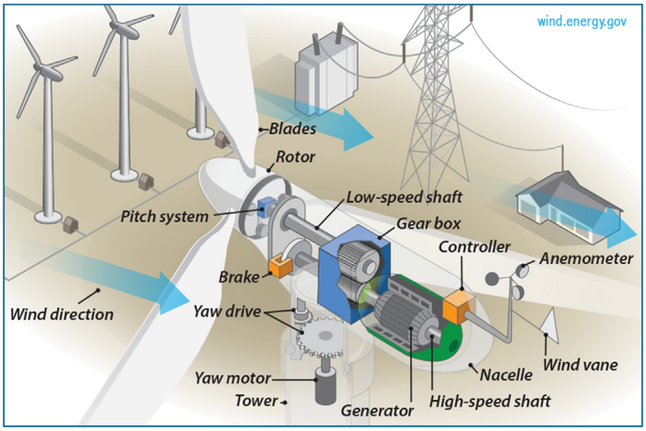

Figure 6.1
The inside of a wind turbine. *Source: Reproduced with permission from EERE (2019).*

6.1 Introduction

Wind turbines are based on the principle of converting the kinetic energy of a wind resource into mechanical work, such as water pumping, or via mechanical work into electricity via a generator (Da Rosa, 2005). Nowadays, wind turbines produced worldwide are almost solely of the electricity-generating type, though mechanical turbines used for water pumping are still of essential use in some areas (Twidell and Weir, 2015). Wind turbines come in a variety of blade designs, but the most common types of wind turbine for electricity generation, both on- and offshore, are horizontal axis turbines with three blades (IRENA, 2018).

Modern-day conventional (horizontal axis) wind turbines are built up from a steel or concrete tower, a yaw system between the tower and the nacelle (the housing for the hub section of the wind turbine) that orientates the wind turbine toward the wind, a drivetrain (gearbox or direct drive generator), a convertor, and the rotor with the blades (Twidell and Weir, 2015). The inner structure of a wind turbine is shown in Fig. 6.1.

The power generated by a wind turbine is related to the quality of the wind, height of the tower (hub height), the rotor diameter, and management of operation and maintenance. In general, wind turbines are able to generate electricity at wind speeds between 3−5 and 25 m/s. The maximum electricity generation is usually achieved from 11 to 25 m/s (IRENA, 2018).

6.2 Market development

Simple devices exploiting the energy available in wind date back thousands of years. The first large wind device for electricity generation was a 12 kW turbine introduced in 1888 in

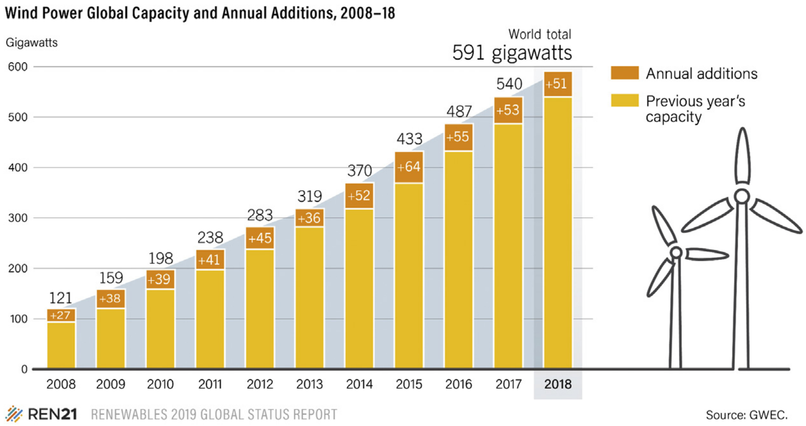

Figure 6.2
Cumulative wind power capacity between 2008 and 2018 (on- and offshore) and annual additions. *Source: REN21, 2019.*

Cleveland, OH, United States. As with many other technologies, renewed interest in wind energy was stimulated by the 1973 oil crisis. While the first developments of wind energy were mainly in the United States (most notably California), market activity shifted to Europe from 1990 onward (Kaldellis and Zafirakis, 2011). More recently, the United States regained a leading position, together with China (REN21, 2019).

In the last 10 years, wind energy has grown from an installed capacity of 121 GW in 2008 to 591 GW in 2018, with about 568.4 GW onshore and the rest operating offshore (REN21, 2019). The current market is dominated by deployment in Asia, and especially China (see Fig. 6.2), being the largest regional market for 9 years straight. China is the largest in terms of both installed capacity and capacity growth. Wind power provides a substantial share of electricity in a growing number of countries. In 2018 wind energy contributed about 14% to the EU's electricity consumption. Higher shares were achieved in at least six EU member states, including Denmark, which met 40.8% of its annual electricity consumption with wind energy (REN21, 2019).

On the supplier side of onshore wind turbines, activities are concentrated at a number of manufacturers in China, the EU, India, and the United States. The largest turbine manufacturers in 2018 were Vestas (Denmark), Goldwind (China), Siemens Gamesa (Germany/Spain), and GE (United States) (GWEC, 2019).

The costs of turbines generally represent 64%–84% of total installed system costs for onshore wind farms. Besides turbines, major cost components include construction and foundation work, grid connection, land, and project costs. Prices of wind turbines were lowest in 2000–04 and rose for some years afterward. The increase occurred because of several factors that are as follows: higher material and labor costs, more demand than supply, and development of larger wind-turbine technologies, leading to higher construction costs (Bolinger and Wiser, 2012). After prices peaked between 2007 and 2010, a downward trend started again. Between 2009 and 2017, turbines with rotor diameters smaller than 95 m showed price declines of 53%, prices of turbines with rotor diameters more than that size declined by 41%. In 2017 average wind turbine prices were less than 1000$/kW in most markets, returning to capital cost levels last seen in 2002 (IRENA, 2018).

In the IEA World Energy Outlook 2018 the global installed wind capacity is expected to increase to 1066 GW in 2030 and 1350 GW in 2040, when accounting for current and announced policy plans. In the alternative scenario where global temperature increase is kept to 2°C, installed capacity increases to 1712 GW in 2030 and 2819 GW in 2040 (also including offshore wind). Together with solar photovoltaics (PV), wind energy is expected to contribute two largest shares to the renewable portfolio (OECD/IEA, 2017). For comparison, IRENA estimates that a total wind capacity of 5445 GW is expected by 2050, of which 4923 GW is onshore and 521 GW offshore (IRENA, 2018).

6.3 Trends in capital expenditures and levelized cost of energy

The cost of installed wind turbines and projects has been declining more or less continuously between the 1980s and 2002 and between 2009 and 2017. In the intermediate time period, there were several factors idiosyncratic to wind power (explained in the previous section) that caused the installed costs of turbines and projects to temporarily increase. Generally, it can be stated that the overall reductions in the levelized cost of wind energy, in the first two decades after the introduction of modern wind turbines in the early 1980s, were driven in large measure by the reduction of installed costs, or upfront capital expenditures (Capex), which was in turn mainly driven by the spectacular increase in size, whereas typical wind turbines capacities were around 10−50 kW in the early 1980s, the largest turbines reached 2 MW in the early 2000s. Due to the economies of scale, use of higher wind speeds at greater height, and other factors, there was a decline in the levelized cost of electricity (LCOE) for more than 400−600$$_{2014}$/MWh in the early 1980s (Wiser et al., 2016) to about 60−80$$_{2014}$/MWh in the early 2000s in the United States (Wiser and Bolinger, 2018); generally consistent trends are observed in many other countries (IRENA, 2019; Wiser et al., 2016).

After 2000 the trend of increasing wind turbine capacities slowed down for onshore wind (however, rapid turbine capacity increases continued offshore, see Chapter 7). While nameplate capacity, hub heights, and blade lengths all grew, growth was slowed, in part, due to the logistical challenges of delivering increasingly large components to sites. A second factor potentially limiting turbine size increase is the visual obstruction of landscapes (including production of noise and casting of moving shadows), which limits the

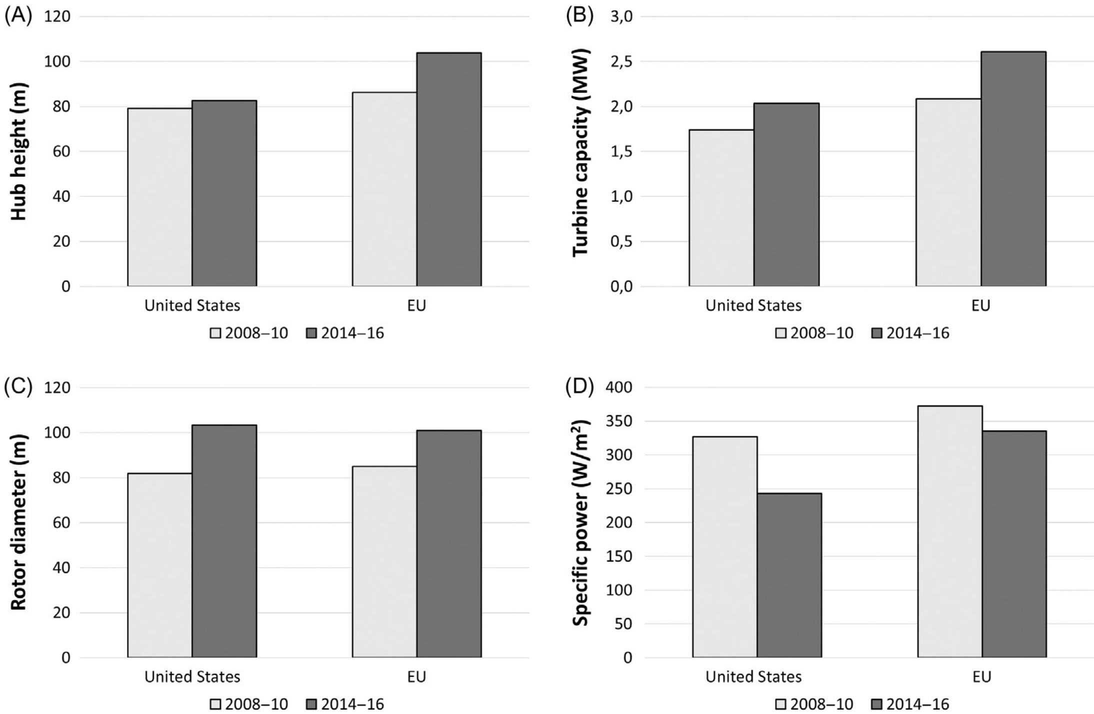

Figure 6.3

Technology trends in EU and the US (weighted averages) for the periods 2008–10 and 2014–16: (A) hub height; (B) turbine nameplate capacity; (C) rotor diameter; (D) turbine specific power. *Source: Derived from Duffy et al. (2019), based on data from IEA Wind Task 26 (The Cost of Wind Energy).*

number of possible sites in densely populated areas and is related to public resistance to wind energy. Nowadays, weighted average installed capacities are approaching 2.5 MW in the United States and between 2.5 and 3.5 MW in many European countries, with hub heights around 80–130 m (see Fig. 6.3). While this is still roughly a doubling compared to the early 2000s, the growth trend has clearly slowed down compared to the 20× factor in capacity increase observed between 1980 and 2000. Nonetheless, Duffy et al. (2019) find that capital costs have generally fallen between 2006 and 2016 in the EU and the United States, from a range of approximately 1100–2100 to 1200–1600€/MW. Of the countries analyzed the largest cost declines were observed in the United States (27%) to a level in line with EU countries. Globally, average costs reached 1500$/kW in 2018, with costs as low as 1200$/kW in China and India (IRENA, 2019).

Duffy et al. (2019) also find that, especially in the EU, recently installed wind parks are at sites with somewhat lower average wind speeds compared to the past, most likely due to the fact that the best sites are already occupied. Yet at the same time, they find a pronounced increase in capacity factor, from 22%–36% in 2008–10 to 27%–42% in 2014–16. In other words, while new wind projects are often installed at sites with somewhat lower wind speeds, overall capacity factors have increased due to taller towers and longer blades. For comparison, capacity factors were around 18%–22% in the 1980s and the first half of the 1990s (Williams et al., 2017). This trend toward higher capacity factors is not restricted to Europe and the United States but is instead a global phenomenon (IRENA 2019).

Duffy et al. (2019) also show downward pressure on operational costs (Opex), from approximately 45–60 to 40–50 €/kW-year over the 2008–10 to 2014–16 periods. Wiser et al. (2019) conducted a dedicated study on operational cost developments in the United States reaching even further back, finding all-in lifetime Opex reductions from approximately 80$/kW-year for projects built in the late 1990s to roughly 40$/kW-year for projects built in 2018. Turbine operations and maintenance (O&M) costs—inclusive of scheduled and unscheduled maintenance—represent the single largest component of overall Opex and the primary source of cost reductions over the last decade.

Duffy et al. (2019) also investigated the change in weighted average cost of capital (WACC): the period-average real after-tax WACCs fell for all countries studied, from a range of 2.9%–5.6% (2008–10) to 1.2%–4.6% (2014–16). This is attributed to the internationally low cost of finance and to the growing perception of wind energy as a mature technology by finance institutions, thus resulting in lower project-risk premiums. The latter is a spin-off from technological learning and could be considered a form of "financial" learning, which may also be relevant for other technologies, for example, offshore wind (Egli et al., 2018).

Overall, it is clear that many different factors have influenced the LCOE in the past decade. Fig. 6.4 depicts the contribution of capacity factor, Capex, Opex, and WACC to reduction in LCOE between 2008–10 and 2014–16 for the EU (averaged) and the United States.

As can be seen from Fig. 6.4, there are two dominant factors that have driven down LCOE in the past decade: reduced Capex and increased capacity factors, with generally less significant contributions from improvements in WACC and Opex. It must be stressed that these are averages, and that on a country basis, the contributions of each factor may vary, and the overall LCOE reduction may also be significantly different than the average 35€/MWh shown for both the EU and the United States. Also, this graph does not take into account country-specific tax regimes. When these are factored in, Duffy et al. (2019) find LCOE as low as 34€/MWh for Denmark and as high as 68€/MWh in Ireland over the 2014–16 period. Using even more recent data, IRENA (2019) reports a global average wind LCOE of 54$/MWh in 2018, whereas Wiser and Bolinger (2019) report the average in the United States in 2018 as 38$/MWh.

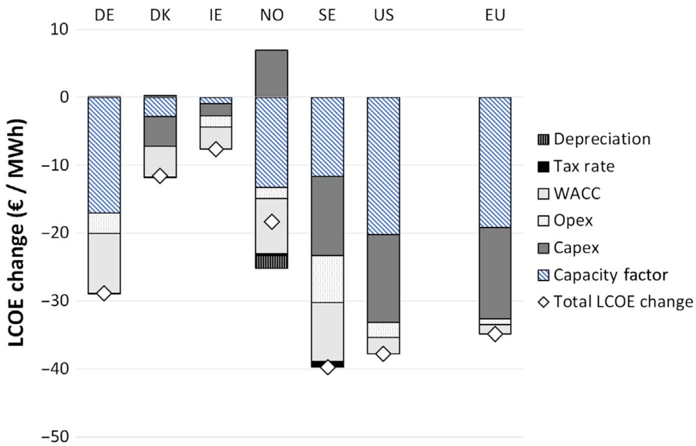

Figure 6.4
Contribution of input variables to changes in average national LCOEs between 2008–10 and 2014–16 periods for various EU member states, the EU as an average and the United States. *DE*, Germany; *DK*, Denmark; *IE*, Ireland; *NO*, Norway; *SE*, Sweden. *Source: Duffy et al. (2019).*

From the earlier statement, it can be concluded that the overall LCOE of onshore wind energy has declined substantially and that the most important drivers for the cost decline were the reduction in Capex and increasing capacity factor. Thus any tools/experience curves solely focusing on Capex as a representation for the cost of wind energy are increasingly missing important contributions from other variables, discussed in more detail in the next section.

6.4 Experience curves for onshore wind energy

Together with solar photovoltaics, onshore wind energy is likely the most extensively studied technology for experience curve analyses. Since the mid-1990s, dozens of studies have been published, covering technological progress curves for onshore wind energy from many different angles. The scope of the studies varies in terms of time series analyzed, geographical scope (e.g., national or global analyses), the use of one-factor (capacity) learning curves or multifactor learning curves (typically also taking R&D expenditures into account), analyzing either the costs of wind turbines, installed wind parks, or (in few cases) the LCOE. This chapter does not aim to provide a comprehensive overview of these studies; for this, we refer to Junginger et al. (2009) for older studies and two meta-analyses (Lindman and Söderholm, 2012; Rubin et al., 2015) for more recent studies. However, this body of work finds a wide range of learning rates: Williams et al (2017) summarize the literature, showing a full range from −5% to 35%, with most learning rates reported between 5% and 10%. This wide variation arises from three main factors: (1) differences in start and end dates, (2) which country's data (or global data) are used, and (3) what type of experience curve model is used. The dates of the studies reviewed in Williams et al. (2017) range from 1980 to 2010, with many focusing on the 1990–2000 period. Countries studied include Denmark, Germany, Spain, the United Kingdom, and the United States, 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, or those that focus on production or LCOE, are also represented.

There are three primary considerations to evaluate when constructing a technological progress model for wind power: the temporal scope, the geographical scope, and the structure of the model. Earlier studies where date ranges for data were constrained resulted in estimated learning rates far from the consensus values. It is thus important to choose a data set with the longest possible coverage (and hence the greatest number of cumulative doublings of capacity) in order to derive meaningful trends least affected by temporary outlier effects. Fig. 6.5 illustrates the reasons why using data from short-time series is tricky: using data from 1982 to 2016 gives a learning rate of around 6%. If one were to instead use recent data from 2009 onward only, one would find learning rates between 24% and 26%, much higher than for, for example, PV, and it would seem unrealistic compared

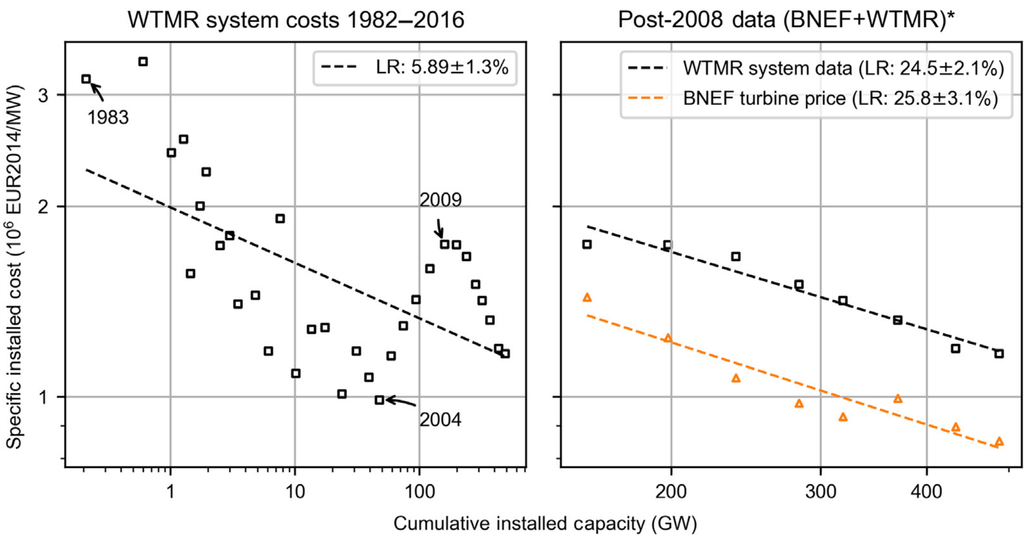

Figure 6.5
Overview of onshore system and turbine price data and experience curves. (Left) Whole dataset from WTMR (Wiser and Bolinger, 2017). (Right) Post-2008 data from Wiser and Bolinger (2017) and BNEF wind turbine price index (BNEF, 2017). *Note that the curves on the right are only shown as an example of short term datasets, and the learning rates shown are not recommended to be used in any modeling activity.

to the long-term trend. On the other hand, using data between 2004 and 2009 would yield negative learning rates—an even more unlikely rate of long-term learning given the data before and after this time period.

Similarly, it is logical that a global scope best fits this technological system: modern wind turbines and wind parks have been deployed globally since the 1980s, with 15 wind turbine manufacturers typically covering more than 90% of the global market at any given time (GWEC, 2019), all using the same basic technological concept (the pitch controlled, three-blade horizontal axis turbine). It therefore seems appropriate to assume that technological learning of onshore wind energy can be best measured using global deployment.

The third point, the modeling approach used, particularly the explanatory variables included, warrants additional discussion. The first issue is whether to rely on a single dependent variable (typically installed capacity) or attempt to disentangle different factors driving technological learning and associated reductions in production cost using a multifactor learning curve approach. Several studies have been published separating cost reductions into learning-by-doing and learning-by-research (Miketa and Schrattenholzer, 2004; Klaassen et al., 2005; Jamasb and Koehler, 2007; Söderholm and Sundqvist, 2007; Ek and Söderholm, 2010). Learning-by-doing rates often vary from 1% to 17%, whereas learning-by-research varies from 5% to 27%. However, these studies often suffer from limited data availability and are typically not able to include the impact of private R&D expenditures. This analysis therefore focuses on single-factor learning curves.

The vast majority of studies use installed capacity as the independent variable and the installed cost of wind turbines or entire wind parks as the dependent variable. This has been the primary focus of the historical literature for several reasons: data availability (cost/prices of wind turbines and wind parks have been collected for many countries and world regions), consistency with experience curves for other renewable energy technologies (e.g., for PV, almost all existing experience curves are also based on upfront costs, most often just for PV modules), and the fact that, between the mid-1980s and 2004, there was a continuous decline of turbine and wind park upfront costs, as shown in Fig. 6.5, typically yielding learning rates between 10% and 20%. The latter trend changed fundamentally with the observed increases in upfront costs between 2004 and 2009 (see Fig. 6.5). While upfront costs have declined between 2009 and 2019 and have reached 2004 levels again, it is hard to argue that upfront costs consistently followed the learning curve observed before 2004. Partly, this can be explained by factors such as increased demand for wind turbines and increased raw material prices between 2004 and 2009 (see the previous section), yet the fact that capital costs in 2017 have only fallen back to those in 2004 requires further explanation.

So, given the strong fluctuations observed in the past 15 years, is the long-term trend with learning rates of about 5.8% (Figs. 6.5) to 6.5% (Fig. 6.6A) for onshore wind reliable? Is it

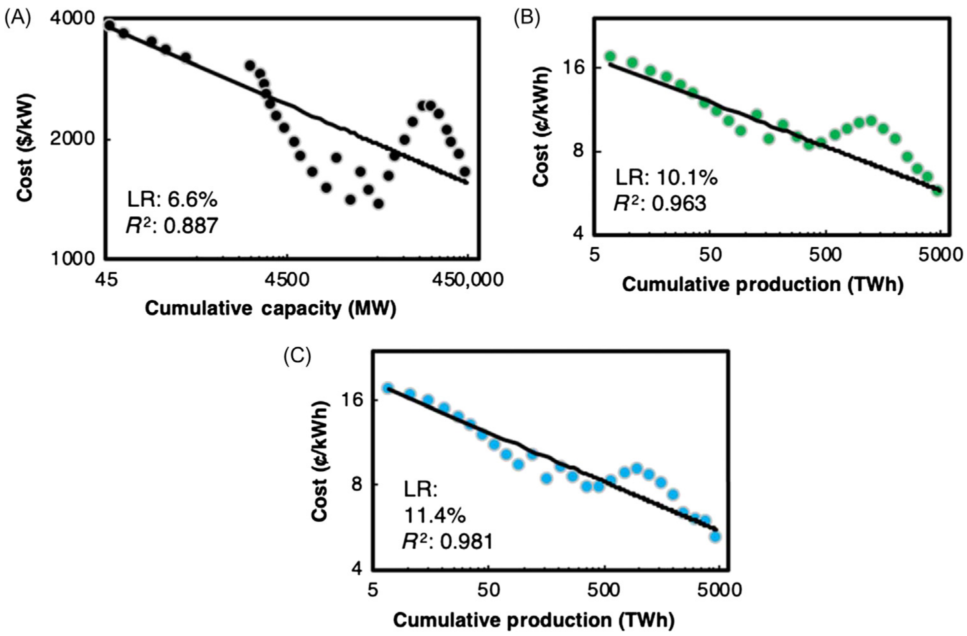

Figure 6.6

Global experience curves for wind power costs in three different models, in log–log scale, with LR and R^2 value reported. Model A considers only power capacity of plants, model B tracks total energy generated (accounting for capacity factor improvements), and model C removes the effect of changes in quality of wind sites. The data for (A) covers years 1984–2017; for models (B) and (C), the range is 1990–2017 (due to lack of data on capacity factors before that period). Costs are shown in real $\$_{2017}$. *LR*, Learning rate. *Source: Adapted from Williams et al. (2017).*

the best model for estimating future cost developments? To answer these questions, we refer to Section 6.3, where some of the underlying factors of the levelized cost of energy reductions observed in the 2006–16 period are discussed. As shown in that section, during this period, many wind parks were placed at sites with somewhat lower wind speeds (presumably because the sites with higher wind speeds had already been occupied). The geographical potential for wind energy in the world is limited, and as a general rule, sites with lower wind speeds will ultimately deliver higher LCOE. While this effect in itself has little to do with learning, the fact that this trend has been paired with a strong increase in capacity factors is very much linked to learning. However, this effect cannot be measured using the traditional method of using upfront cost of capacity as the dependent variable. As a related argument, it is clear that the primary aim of wind plant operators (and, indirectly, wind turbine manufacturers) is not to build *capacity* at lowest cost but to produce *electricity* at the lowest possible cost. This may not necessarily be at the lowest upfront cost of capacity, as higher per-MW capital costs might allow for improvement in other factors that affect the primary design variable (LCOE): capacity factor of the plant, operational costs, and financing costs. Perhaps most importantly, the sizable increases in tower heights and the longer blades that are hallmarks of modern wind turbines have yielded sizable increases in the capacity factors of wind plants, helping to contribute to lower LCOE.

Given these considerations, a small but growing literature has emphasized the need to develop learning curves based on the levelized cost of wind energy. Whereas recent analyses suggest historical global learning rates of 6%−9%, when considering only the upfront costs of land-based wind (IRENA, 2018; Wiser et al., 2016), LCOE-based learning rates have been shown to be higher, typically ranging from slightly less than 10% to nearly 20% given the greater number of cost-reduction drivers considered (Wiser et al., 2016; Williams et al., 2017; IRENA, 2018).

Focusing on the approach used in Williams et al. (2017), this study develops three different experience curve models, using global installed capacity/electricity produced as independent variables and US data on the cost of land-based wind (as proxy for global costs) as the dependent variable:

1. Capacity model—upfront capital cost ($/W) versus total capacity (W)
2. Generation model—LCOE ($/kWh) versus cumulative generation (kWh)
3. Wind quality−adjusted generation model—levelized cost assuming same wind site quality ($/kWh) versus cumulative generation (kWh)

This method attempts to account for all factors that are related to learning while controlling for changes in those factors that affect LCOE but are unrelated to learning. This includes changes in reference wind quality for individual years, and the average capacity factors for each year for new wind parks. Global capacity and cumulative generation are global totals, given lack of global data, US prices, capacity factors, and wind site quality were used as proxies. A discount rate of 7% and a lifetime of 20 years are assumed for all calculations of LCOE. For the detailed method and data sources, we refer to the underlying publication in Williams et al. (2017), and the focus here on the results, shown in Fig. 6.6.

As seen in Fig. 6.6A, the experience curve using the upfront installed cost of capacity as the independent variable (model A) shows a pattern similar to Fig. 6.5. Sensitivity analysis revealed that the capacity-based learning rate is very sensitive to the chosen starting and end years. The R^2 of the fitted trend improved successively for models B and C, and the average learning rate increased about 10%−11%. The C model has the highest R^2 value, 0.981, with an average learning rate of 11.4% and confidence interval of 10.9%−12.0%. Models B and C were shown to be much less sensitive than model A to starting and end point years for the data series. Thus taking into account the additional factors driving overall LCOE reductions led to an improved experience curve and a significant narrowing of the range in learning rates.

Three factors that Williams et al. (2017) did not account for were cost reductions in Opex post 2006, changes in project lifetime, and the cost of finance. Wiser et al. (2019) find that when plotting historical Opex against cumulative global installed capacity, a 9% Opex learning rate is reached. That work also concluded that expected project design lives have increased from 20 years to 25–30 years; this lowers LCOE by about 4%–6% with a 7% discount rate. Thus the learning rate of about 10% cited earlier could be even (slightly) higher; the same would also be true if the effect of technological maturity on the cost of finance was considered.

6.5 Data collection and methodological issues

An overview of the general data collection issues applicable to wind energy is given in Table 6.4. There are no publicly available data for the production cost of wind turbines or wind parks, and so the use of market prices is very common for onshore wind. Price trends ought to follow costs over the long term, but there can easily be deviations over shorter time periods. For example, prices were inflated in the period of 2004–08 when wind demand clearly exceeded supply, and a number of other exogenous influences impacted prices. Care is thus needed using price as a proxy for underlying production costs. Also, as argued in the previous section, the upfront cost of capacity is increasingly becoming an inadequate metric to capture the overall technological learning of onshore wind—elements such as higher capacity factors, lower O&M costs, longer design lives, and lower interest rates (as a consequence of increased trust in onshore wind technology) are not reflected by this metric. By taking into account (some of) these factors in an experience curve for electricity, a more accurate model to project future LCOE developments can be achieved. Further research should therefore focus on this formulation.

Table 6.4: General data collection issues for onshore wind power.

Issue	Resolution	Applicability
Production cost data is unavailable	Price data are used	fx1
Data not directly reported/available for desired cost unit (LCOE)	Estimating LCOE from upfront capacity cost, capacity factor, and other variables	fx1
Data only available for limited geographical scope, while technology is deployed globally	Different datasets combined and compared	fx1
Data are in different currencies or currency year	Convert currency and correct for inflation	fx1
Early cumulative production figures are not agreed upon or available		
Supply/Demand affecting costs significantly	Use long-term trends; try to control and correct for exogenous price drivers, or exclude periods in which prices are driven by demand	fx1

LCOE, Levelized cost of electricity.

Finally, there is a geographical component to LCOE for onshore wind, that is, there are sites with low and high production costs, depending in part on average wind speeds, accessibility, and possibilities to connect to the grid, etc. Typically, the low-cost sites would be expected to be occupied first, with higher cost sites used later on. This effect will, to some extent, cancel out learning effects—yet the previous sections have shown wind turbine designs can be optimized for such sites, leading, thus far, to continued reductions in average LCOE. If and how long this trend will continue is subject to uncertainty.

6.6 Discussion, conclusion, and future outlook

Based on the findings presented earlier, it has become clear that using upfront capital cost as the basis for experience curves for wind energy may result in increasingly inaccurate estimates regarding the past (and future) cost reduction of electricity from onshore wind parks. Unless improvements in, for example, capacity factor and O&M costs are estimated exogenously, using capacity-only experience curves may result in a serious underestimation of the potential future LCOE reductions that may be achieved.

Based on the Opex learning rate derived by Wiser et al. (2019), a further \$5−\$8/kW-year (12%−18%) Opex reduction from 2018 to 2040 is projected. When compared with the broader literature, these findings suggest that continued Opex reductions may contribute 10% or more of the expected reductions in land-based wind LCOE. Moreover, these estimates may understate the importance of Opex owing to the multiplicative effects through which operational advancements influence not only O&M costs but also component reliability, performance, and plant-level availability—thereby affecting levelized costs though Opex reduction and by enhancing annual energy production and plant lifetimes. Beyond Opex, further improvements in project performance, project life, and the cost of finance can also be expected (Wiser et al., 2016), confirming the inadequacy of learning rates based solely on upfront costs.

Using global wind adoption rates from the 2018 IEA New Policies Scenario (IEA, 2018), combined with a 11.4% learning rate for the LCOE of wind power, future wind-power prices are projected to 2030. Historical data follow the same method as model C on Fig. 6.6. The projected data in Fig. 6.7 start with an estimated wind power cost of 4.6 \$cents/kWh in 2018 and apply an 11.4% learning rate (see Fig. 6.6) to the installed capacity estimates from the 2018 IEA New Policies Scenario. The 2018 levelized cost of 4.6\$cents/kWh is an average of the 5.4\$cent/kWh estimate from IRENA (2019) and the 3.8\$cent/kWh estimate from Wiser and Bolinger (2019).

In this scenario the price of wind power falls to 3.7\$cents/kWh by 2030, making it highly competitive with expected prices of new coal and natural gas generation. This constitutes a 50% reduction in LCOE between 2011 and 2030, which is quite a bit higher than

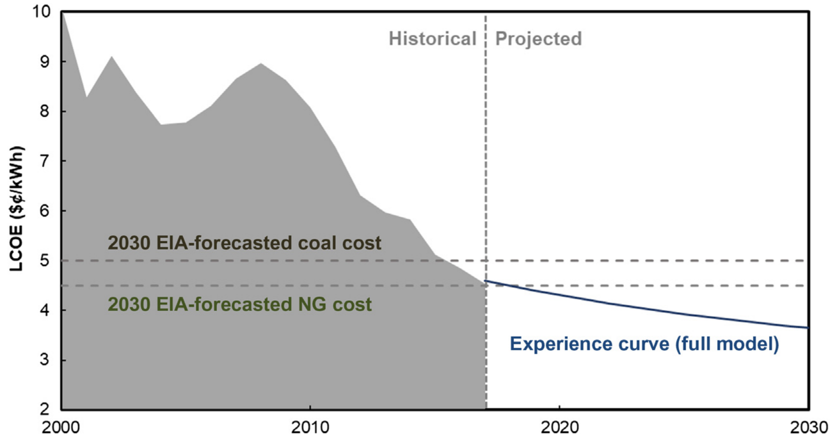

Figure 6.7
Historical and projected onshore wind generation costs (global estimate), with wind generation costs falling to 3.7cents/kWh by 2030.

the 20%–30% reduction described in the IEA report Past and Future Cost of Wind Energy (Lantz et al., 2012). It represents a reduction in LCOE of approximately 25% from 2018 to 2030. Another relevant comparison is an expert elicitation study of future costs of wind power, which yielded a range of implicit future learning rates between 14% and 18% (Wiser et al., 2016). While there is overlap in results from learning curves and expert elicitation, the 10%–12% learning rate estimated here yields less bullish prospects for cost reductions. This distinction can be partly explained by the fact that there are a few factors still excluded or partially excluded from the learning rate analysis (specifically, improvements in project lifetime, Opex costs, and financing costs).

Considering all of these factors together and leveraging the best available current research, the long-term learning rate for the LCOE from onshore wind power is estimated to be at least 10%–12%, with higher estimates possible if additional cost-reducing drivers are considered. However, history has shown that external effects can temporarily shift LCOE far from the long-term trend, so considerations of supply and demand, labor and material costs, or changes in finance structure are relevant to translating the underlying learning effects to actual market prices.

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