

How Are Future Energy Technology Costs Estimated? Can We Do Better?

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ABSTRACT

Making informed estimates of future energy technology costs is central to understanding the cost of the low-carbon transition. A number of methods have been used to make such estimates: extrapolating empirically derived learning rates; use of expert elicitations; and engineering assessments which analyse future developments for technology components' cost and performance parameters. In addition, there is a rich literature on different energy technology innovation systems analysis frameworks, which identify and analyse the many processes that drive technologies' development, including those that make them increasingly cost-competitive and commercially ready. However, there is a surprising lack of

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linkage between the fields of technology cost projections and technology innovation systems analysis. There is a clear opportunity to better relate these two fields, such that the detailed processes included in technology innovation systems frameworks can be fully considered when estimating future energy technology costs.

Here we demonstrate how this can be done. We identify that learning curve, expert elicitation and engineering assessment methods already either implicitly or explicitly incorporate some elements of technology innovation systems frameworks, most commonly those relating to R&D and deployment-related drivers. Yet they could more explicitly encompass a broader range of innovation processes. For example, future cost developments could be considered in light of the extent to which there is a well-functioning energy technological innovation system (TIS), including support for the direction of technology research, industry experimentation and development, market formation including by demand-pull policies and technology legitimisation. We suggest that failure to fully encompass such processes may have contributed to over-estimates of nuclear cost reductions and under-estimates of offshore wind cost reductions in the last decade.

Keywords: Energy technologies; technology innovation system frameworks; technology cost reductions; technology innovation policies

JEL Codes: O31, O33, Q55, Q58

1 Introduction

Energy technology cost projections are central to estimates of the economy-wide costs of reducing greenhouse gas emissions. This is almost tautological, given that the majority of integrated assessment and energy systems models operate on a least-cost optimisation objective, whereby future climate targets are met with the lowest cost mix of

energy technologies (Clarke *et al.*, 2014; Farmer *et al.*, 2015; Pfenninger *et al.*, 2014). It stands to reason that changing energy technology cost assumptions will change the mix of technologies chosen by these models, as well as the overall costs of mitigation (Barron and McJeon, 2015; Bosetti *et al.*, 2015; Giannousakis *et al.*, 2020; McJeon *et al.*, 2011; Muratori *et al.*, 2017). This is an important consideration, given the centrality of mitigation cost estimates in prominent analyses of climate change action (e.g., IPCC, 2014; Stern, 2007).

Recent years have seen a growing body of literature on estimates of future energy technology costs, using various methods such as (most prominently) learning curves and expert elicitations. Learning curves (Forster *et al.*, 2013; Neij *et al.*, 2003; Rubin *et al.*, 2015) most commonly link cumulative technology deployment to technology cost or price. Learning curve analysis is usually presented with the caveat that deployment alone does not cause technology cost reductions, although it may be closely correlated with it, but nevertheless its use can mask the underlying complexity of the innovation processes at work. Understanding these processes is likely to be critically important to ensuring that learning curves are used in an appropriate way. This includes a consideration of different stages of technological maturity, which may be associated with different rates of learning, as well as any potential limits to future cost reductions, such as material supply bottlenecks or fundamental efficiency and performance limits, that might prevent technologies from reducing in cost in the future as they have done in the past.

In addition to the widespread use of learning curves, there is a growing use of expert elicitations in energy technology cost projections (Verdolini *et al.*, 2018; Wiser *et al.*, 2016; Baker *et al.*, 2015a). As discussed in this paper, the majority of existing expert elicitations explore the dependency of future technology costs on different levels of research and development (R&D) funding, whereas — as is implicit in most learning curve analysis — deployment also has a considerable role to play. Reflecting on how expert elicitations might be better adapted to capture a wider range of innovation processes is therefore worthwhile, at a time when a raft of immature, pre-commercial and highly novel technologies without a meaningful cost reduction history are being considered for their future cost reduction and mitigation potential.

As well as this literature on future energy technology cost estimates, there is a well-established literature on frameworks that encompass

the different processes of innovation for energy technologies. Most prominent is energy technology innovation systems (TIS) analysis, which offers a systemic perspective encompassing technology development stages, major innovation processes, actors, institutions and networks (Gallagher *et al.*, 2012). This lends insight on how and why particular energy technologies have succeeded, or failed to succeed, in achieving innovation, commercialisation and penetration into energy systems in given geographical contexts. A central element of this and other innovation system frameworks involves understanding how support for technologies by policies, institutions, entrepreneurs and other actors has allowed them to become commercially cost-competitive over time.

As demonstrated in this paper, prominent methods to estimate future energy technology costs have in some cases (using the examples of nuclear and offshore wind) performed rather poorly when compared to actual technology cost developments. Furthermore, in these cases there was relatively little explicit incorporation of the insights and considerations of TIS frameworks, which may in retrospect have helped improve the accuracy of these future cost estimates.

In fact somewhat surprisingly and as described in this paper, the fields of energy technology future cost estimation and technology innovation systems analysis are only weakly connected. The former tends to focus on deriving quantified estimates of future technology costs, often with implicit recourse to innovation processes, such as the learning-by-doing processes represented by cumulative deployment, or the research and development (R&D) processes represented by research funding or patent counts, but without sufficient explicit discussion of the implications of different technology innovation systems and processes.

This paper explains how this important gap can be bridged, by first discussing how future energy technology costs are most commonly estimated, as well as the many limitations and criticisms associated with each of the different methods employed. It next describes a variety of commonly used technology innovation systems frameworks focused on understanding the innovation journey and processes. By doing so, the paper identifies the different ways in which these technology innovation systems frameworks are able to assist in future energy technology cost estimates.

A number of other recent studies have sought to shed light on how different factors and innovation processes drive cost reductions in energy

technologies. For example, Elia *et al.*'s (2020) review into how different drivers of innovation relate to pre-eminent methods of cost estimation (one-factor learning curves and bottom-up cost models) highlights how several critical factors of technologies' development stages are not captured in such methods. They show that market dynamics and learning through interactions between different stakeholders are particularly poorly captured, and explicitly call for a closer integration with innovation studies to better develop the field of future cost estimation. Thomassen *et al.* (2020), focusing on learning curves, make a number of recommendations on better using this technique to estimate future costs, including combining them with expert estimates, as well as a greater focus on the sub-components of individual technologies. Grubb *et al.* (2021) highlight the importance of institutional factors on innovation, including regulatory regimes and networks between technology innovators, users and finance. They suggest it may be fruitful to explore links between quantitative techniques to measure innovation and cost reduction and the qualitative socio-technical literature on innovation. Wilson *et al.* (2020) highlight the multiple benefits (including higher learning rates and returns on innovation investment) of what they term "granular" technologies, which are "small in size, low in cost, many in number, and distributed in application" (Wilson *et al.*, 2020). Sweerts *et al.* (2020) also find that technologies' learning rates are inversely proportional to unit size. Malhotra and Schmidt (2020) identify faster learning in less complex or more mass-customised technologies, providing a picture of how technology typologies can relate to their learning rates and cost reduction prospects. This paper's additional contribution to the studies described above is to detail the many opportunities for looking widely across both future energy technology cost estimation methods and technology innovation systems frameworks, so as to identify the most fruitful links to enrich the former with the latter.

The rest of this paper is set out as follows. Section 2 analyses the different methods commonly used to estimate the future costs of low-carbon energy technologies, with a view to highlighting their strengths and limitations. Section 3 analyses the different frameworks commonly used to identify the processes and actors that drive energy technology innovation and cost reduction. Section 4, building directly from the previous two sections, describes the extent to which underlying drivers of technology innovation — as gleaned from technology innovation systems

frameworks — are currently incorporated (either implicitly or explicitly) into different technology cost estimation methods. It highlights ways in which they can be better incorporated, using two technologies in particular (nuclear and offshore wind) to illustrate the opportunities to do this. Section 5 concludes by discussing the policy-relevance of making future technology cost estimates that are more closely informed by technology innovation systems frameworks.

2 Methods for Estimating Future Technology Costs

There are a number of established methods for estimating future energy technology costs, which have been categorised into two broad approaches: the application of “learning curves” and “engineering assessments” (Gross *et al.*, 2013). The latter approach, which tends to consider technologies in terms of their separate components, is often combined with expert assessments of how the costs and performance of these components could change over time. However, eliciting views from experts on whole technology costs has become an increasingly common approach in its own right, which is why in this section expert elicitations are presented as a separate, third method, in addition to the learning curve and engineering assessments.

Additional methods are used in technology cost and performance forecasting, including productivity analysis techniques such as data envelopment analysis (DEA) (Charnes *et al.*, 1978). This allows the determination of how production frontiers, which represent the most efficient combination of product inputs into outputs, have shifted over time, thereby determining changes in underlying unit costs of production in firms, systems or technologies. Here we do not include an evaluation of the performance of such techniques, rather focusing our attention on the dominant methods that have been applied to the projection of specific low-carbon technology costs in recent years.

2.1 Learning Curves

To date, the most prominent method for low-carbon technology cost projections is the use of single-factor learning curves, which relate technology cost to cumulative technology deployment levels. Learning curves most commonly demonstrate a fixed percentage fall in technology cost

for each percentage increase in cumulative deployment, such that a doubling of deployment leads to a fall in cost of $(1 - \text{the "progress ratio"})$. So a progress ratio of 0.8 means that there is a 20% cost reduction for each doubling of deployment. This 20% value is known as the learning rate.

Learning curve relationships have been witnessed for several decades. The IEA (2020) describes how Wright's (1936) discussion of aeroplane manufacture, in which cost inputs (labour and materials) were observed to fall exponentially with cumulative production, gave rise to the term "learning curve".¹ This was followed by Arrow's (1962) generalisation of the learning effect and assertion that technical change can be ascribed to experience, and Boston Consulting Group's (1970) extension of cost inputs to include all manufacturing inputs as well as any other costs required to deliver the product to the end-user. This firm historical basis (on the strength of empirical observations) for learning curves has made their use widespread.

But learning curves have been subject to a range of criticisms, concerns and cautions. These have been widely documented and include: the lack of a firm theoretical basis (Ibenholt, 2002; IEA, 2000); dependence of derived learning rates on the data series and time period considered (McDonald and Schrattenholzer, 2001; Parente *et al.*, 2002; Yu *et al.*, 2011; Zheng and Kammen, 2014); lack of commercially sensitive technology cost data which means that price is relied on as a (imperfect) proxy, reflecting market dynamics rather than underlying innovation (Boston Consulting Group, 1970); failure to account for changes in technology quality (Nemet, 2006); the potential for variable learning rates, with for example lower rates in early deployment of new designs (Yeh and Rubin, 2012) and as cost floors are approached (Kouvaritakis *et al.*, 2000); an uncertain direction of (and possibly bi-directional) causality between deployment and cost reduction (Kahouli-Brahmi, 2008); importance of other factors such as (hard-to-measure) R&D and material input prices (Jamasp, 2007), as well as evidence that time and economies of scale, rather than deployment, are equally good predictors of cost (Nagy *et al.*, 2013); and the possibility that technologies consist of components with different learning rates (Ferioli *et al.*, 2009; Staffell and Green, 2013).

¹In the literature, learning rates are based on production costs, whereas experience rates are based on product prices. However, these terms are sometimes used interchangeably.

There have been many attempts to address these criticisms, such as the inclusion of R&D (Kittner *et al.*, 2017; Kobos *et al.*, 2006; Miketa and Schrattenholzer, 2004; Zheng and Kammen, 2014), as well as other factors including time (Papineau, 2006), scale (Isoard and Soria, 2001; Miketa and Schrattenholzer, 2004; Yu *et al.*, 2011) and material input costs (De La Tour *et al.*, 2013; Yu *et al.*, 2011) in multi-factor learning curves. But whilst these have in some cases better explained past cost reductions, only in limited cases (De La Tour *et al.*, 2013; Kittner *et al.*, 2017) have they been used to estimate future costs on the basis of a wider range of factors.

Table 1 shows a number of estimates of learning rates for some electricity supply technologies, based on models which include both R&D and cumulative deployment as explanatory variables (Rubin *et al.*, 2015). There is a wide range of estimates of even one-factor learning rates for most technologies (the exception being hydroelectric, for which only one study was found). In general, learning-by-doing rates are very different depending on whether they are part of a one- or two-factor model. This derives from the difficulty in obtaining consistent and reliable data on R&D, as well as differences between studies depending on the regions and time periods included in the learning rate estimates (Rubin *et al.*, 2015). This can make it challenging to produce reliable and meaningful insights from these empirically derived learning rate estimates.

As mentioned above, it has long been a limitation of learning curves that they have no good underlying theoretical underpinning (McNerney *et al.*, 2011). For example, although many still point to the fairly persistent learning curve of solar photovoltaics across many decades, the sheer range of values of learning rates (as shown in Table 1) hints at its multiple phases of development, with multiple drivers of innovation and cost reduction. These different phases and drivers are summarised in Figure 1, which is derived from a detailed investigation into the many different applications, policies, R&D and manufacturing advances responsible for solar PV modules' dramatic cost reduction over more than 60 years of development (Gambhir *et al.*, 2014; Nemet, 2019). Such complexity cannot easily be theoretically captured in one-factor (or even two-factor) learning curves.

Table 1: One-factor (learning by doing only) and two-factor (also including R&D) learning rates for selected electricity generation technologies.

	One-factor models			Two-factor models			Years covered across all studies		
	No. of studies with one factor	No. of studies with two factors	Range of learning rates	Mean LR ¹	Range of rates for LBD ²	Mean LBD ² rate		Range of rates for LBR ³	Mean LBR ³ rate
Natural gas combined cycle	5	1	-11% to 34%	14%	0.7% to 2.2%	1.40%	2.4% to 17.7%	10%	1980-1998
Onshore wind	12	6	-11% to 32%	12%	3.1% to 13.1%	9.60%	10% to 26.8%	16.50%	1979-2010
Offshore wind	2	1	5% to 19%	12%	1%	1%	4.90%	4.90%	1985-2001
Solar PV	13	3	10% to 47%	23%	14% to 32%	18%	10% to 14.3%	12%	1959-2011
Hydro-electric	1	1	1.40%	1.40%	0.5% to 11.4%	6%	2.6% to 20.6%	11.60%	1980-2001

Notes: Reproduced from Rubin *et al.* (2015); ¹LR = Learning rate; ²LBD = Learning by Doing; ³LBR = Learning by Research; some one-factor studies report multiple values based on different datasets, regions, or assumptions.

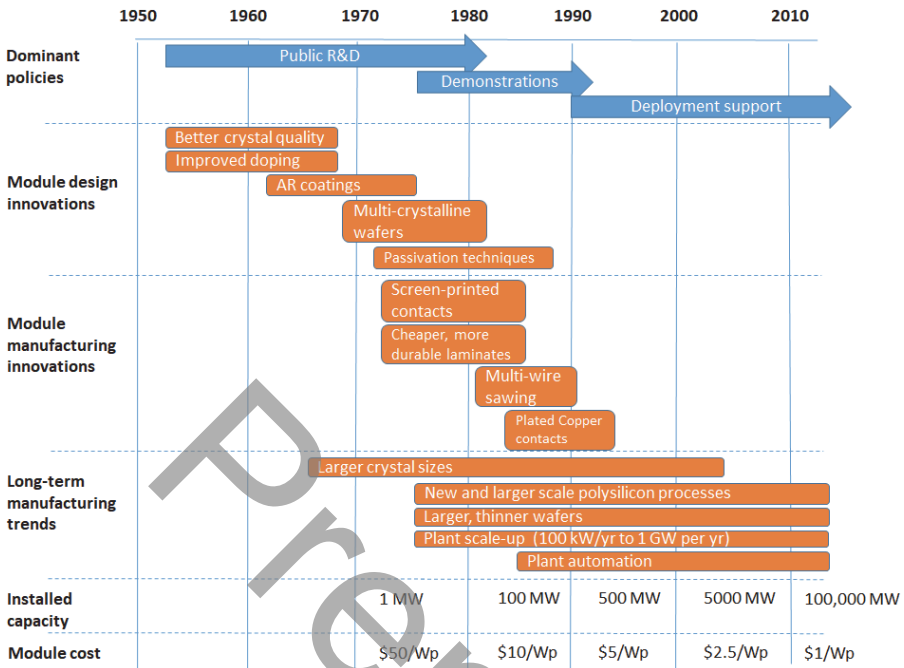


Figure 1: Major policy drivers behind, and technical improvements in, solar PV modules, 1950–2010.

Source: Reproduced from Gambhir et al. (2014).

Over the past decade, significant strides have been made towards better understanding the theoretical potential of technologies to travel down the learning curve, in terms of their design complexity (McNerney et al., 2011), level of granularity (Wilson et al., 2020), unit size (Sweerts et al., 2020) and the combination of design complexity and customisation versus standardisation (Malhotra and Schmidt, 2020). These taxonomies of technologies and their associated learning rates open up promising avenues to better understand how such rates relate to underlying technology properties.

Nevertheless, the key problem remains that learning curves based on historical data may not be good predictors of the future, since the processes governing future cost reductions could be different to those governing past cost reductions. This is why greater insight into possible future processes is needed in order to make better cost projections.

In summary, learning curves are a widely used and (at least in their single-factor form) simple method of approximating how technology costs could fall with increased levels of future deployment, and less commonly with a range of other factors including R&D, elapsed time and economies of scale. The multi-factor learning curve models, in particular, are more representative of the multiple factors involved in the process of innovation as discussed in Section 3, since they ascribe separate cost reduction impacts to deployment-related factors and R&D-related factors. However, the complexity of the innovation process, which sees ongoing feedbacks and synergies between R&D, deployment and a range of other factors and policies, is not easy to capture in such learning curve relationships, either from a theoretical or data availability perspective. In addition to the other shortcomings highlighted above, this means that learning curves should not be relied upon as the sole predictor of future technology costs. Sections 2.2 and 2.3 discuss the two other prevalent methods of future technology cost estimations: expert elicitations and bottom-up engineering models.

2.2 Expert Elicitations

Eliciting experts' views on future technology costs is becoming an increasingly common method of cost projections. As well as the multiple shortcomings of learning curves outlined in Section 2.1, expert elicitations have been asserted by several researchers to be a critical tool for estimating a range for future developments in technology costs and performance, given that past trends may not be a good guide to future progress, particularly in light of the fact that such progress may derive from unique breakthroughs (Bistline, 2014; Morgan, 2014). The approach has been recommended by the US National Research Council (NRC, 2007) for use by the US Department of Energy to help make funding decisions for R&D programmes. It is also commonly employed in other areas, notably analysis of the climate system, with the IPCC's fifth assessment report frequently marrying expert opinion with scientific modelling results to arrive at likelihood ranges for key climate parameters (Myhre *et al.*, 2013).

Much thought and reflection has been applied to the process of conducting elicitations, which has led to sets of principles for best practice. These include first and foremost how to tackle the issue

of experts potentially being biased in their estimates (Tversky and Kahneman, 1974). The three most common biases considered are:

- “overconfidence bias”, whereby experts are potentially liable to display too much certainty in their estimates, resulting in estimated parameter ranges that are narrower than is realistic;
- “availability bias”, whereby experts tend to rely on knowledge and data that are most readily available to them, rather than considering a complete range of data and knowledge relevant to forming estimates. Such bias could lead to estimated parameter ranges that are not only narrower than but also skewed relative to the full realistic range;
- “anchoring bias”, whereby experts show a tendency to make only limited changes in their initial views or estimates in light of new or updated information. As with the above two biases, this could again lead to overly narrow estimated ranges.

These biases can be minimised through providing background information on the technical and cost characteristics of the technology, so that experts have a broad and up to date summary of information in front of them, thereby minimising overconfidence and availability biases; undertaking elicitations face-to-face rather than remotely (e.g., by e-mail or post), so that the elicitation can be as interactive as possible, thereby allowing potential biases to be challenged and opinions revised; requiring that experts provide ranges of values for costs and other parameters of interest, explicitly stated with likelihoods (e.g., a median, 10th percentile and 90th percentile estimate of the parameter value) and challenging them to consider circumstances under which the range might be exceeded and how realistic that is, which can help tackle overconfidence bias in particular (Bistline, 2014; Morgan, 2014). It is now common practice to apply such techniques in expert elicitation exercises (Anadón *et al.*, 2017, 2012; Bosetti *et al.*, 2012; Catenacci *et al.*, 2013; Curtright *et al.*, 2008; Verdolini *et al.*, 2018).

In addition to these techniques, practitioners of elicitations also stress the importance of interviewing a variety of stakeholder experts from different backgrounds so that both technical and economic knowledge can be brought to bear on future cost and performance estimates

(Morgan, 2014). This is particularly important in the case of technology costs, which can depend heavily on technological progress, but which may be difficult to translate into cost data without a good knowledge of production processes and product markets. As such, use of both academic and industrial experts, as well as more generalist stakeholders such as industry analysts and consultants, is of potential benefit in ensuring a wide sampling of available knowledge. Further good practice, in line with the methods to minimise biases as discussed above, includes a clear explanation of the process to experts both before and during the elicitation (including, crucially, making them fully aware of the biases discussed above), a precise definition of metrics and contexts for the parameters to be elicited, and the provision of visualisation tools, such as scales for parameters which experts can mark in order to state their estimates and if necessary revise following further consideration (Bistline, 2014; Morgan, 2014).

Despite these best practice guidelines, practitioners of expert elicitations readily acknowledge that limitations remain in using this method (Morgan, 2014). As well as the recognition that biases cannot be eliminated, only minimised, a further limitation of this approach is that the very enterprise of eliciting future values from experts assumes that there are appropriately qualified people to give informed opinions about parameters whose values may sensibly and rationally be estimated. The more one moves away from questions whose answers involve matters of fact based on established empirical science and well-validated models and towards areas where individual and social behaviour determine outcomes, the less likely it is that genuine predictive capability exists (Morgan, 2014).

In addition, recent analysis into the process of forecasting suggests that experts in a particular field may not actually be the best forecasters, with certain techniques and practices more important than subject expertise (Tetlock and Gardner, 2015). These techniques include: actively considering all possible factors and uncertainties; considering counter-arguments to initial reasoning; breaking complex estimation tasks into tractable sub-tasks; reacting rapidly to new evidence to an appropriate degree and learning from past mistakes in making estimates which turned out to be far from reality (Tetlock and Gardner, 2015).

In the area of low-carbon technology, the field of expert elicitation is still somewhat nascent in terms of the number of studies undertaken,

though with an increasing array of technologies included in elicitation studies. Baker *et al.* (2015) collate a large number of expert elicitations in recent years (stemming back to 2008) in order to attempt to assess what implications they have for ranges of cost projections of key low-carbon technologies including solar PV, wind, CCS, biofuels and storage. Importantly, each of the 13 studies that are synthesised explores future technology costs in different scenarios of R&D funding and all studies share the (unsurprising) conclusion that increased R&D funding is likely to drive down technology costs. What has not been discussed in these studies is the potential role of increased deployment on future technology costs, a somewhat surprising omission given the prevalence in the energy technology future cost estimation literature of learning curves relating costs to deployment levels. Two studies (Few *et al.*, 2018; Schmidt *et al.*, 2017) have explicitly taken on the mantle of including non-R&D-related factors into future technology costs, as well as R&D funding scenarios, and in so doing lend important insights into the relative efficacy of these different factors in driving future cost reductions.

However, for the most part expert elicitations are arguably not yet a fully formed and fully robust method of future technology cost estimation. They allow experts to consider many different factors that could lead to future technology cost reductions as highlighted by different models of innovation presented and discussed later in Section 3.2. Thus, in principle, they can incorporate a wide range of innovation processes in experts' mental models of how costs might reduce in the future. However, to date they have most commonly given an explicit role to R&D, rather than other drivers of cost reduction.

2.3 Engineering Assessments of Technology Cost Components and Manufacturing Processes

In addition to learning curves and expert elicitations, analysts also employ detailed bottom-up models of technologies (often referred to as engineering assessments), which split the technologies' costs into different components, including material costs, capital equipment costs, utility and other processing costs and financing costs (Gross *et al.*, 2003; Lundquist *et al.*, 2010; Nemet, 2006; Rao and Rubin, 2002). Their utility for making cost projections stems from the principle that it may

be more tractable to make estimates of the costs of separate technology components than the total cost of a complete technology.

In addition and of critical importance, these assessments can help identify how specific technical changes impact on overall technology cost (which is referred to as “parametric modelling” (Gross *et al.*, 2013)), as well as identifying current technological limitations or bottlenecks which might need to be overcome in order to achieve cost reductions (Mukora *et al.*, 2009). This allows engineering assessments to in theory be linked to specific policy levers. For example, if they help demonstrate that fundamental product technical performance improvements would yield the greatest cost reductions, then this could reasonably signify the need for increased fundamental R&D policy support. By contrast, if production scale is the key driver of costs, then this could suggest that market expansion or deployment support policies are required.

This in-depth consideration of technologies can provide detailed insights on important drivers and barriers of cost reduction with associated policy implications. A notable example of such linking has been undertaken in a study of how solar photovoltaics reduced in cost over the period 1980–2012 (Kavlak *et al.*, 2018). In this study the authors identify two periods in which a range of factors (including module efficiencies, material costs, plant sizes and material yields) influenced cost reductions over two distinct periods (1980–2001, 2001–2012), and how in both periods, R&D was highly influential as a driver, whilst in the latter period economies of scale were of almost equal importance. This allows a linkage to specific policies (R&D support, deployment support to drive plant scale) to cost reductions, from which lessons can be learned about further incentivising solar PV, as well as other technologies, down their cost curves.

The potential limitations of the engineering-based approach are that it cannot in itself provide estimates of how individual technology components will change over time, without being combined with expert assessments, learning curves or other projections for those components, which (as discussed in Sections 2.1 and 2.2 above) are subject to their own limitations and challenges. Engineering assessments may also risk overly constraining the view of a particular technology, by considering it in terms of the individual components of its current design, thereby closing off the possibility of considering more fundamental, or radical, design changes (Mukora *et al.*, 2009). Moreover, there is space to

improve the utility of engineering assessments through better representing the uncertainties around the input assumptions on the technology components represented in these assessments (Gambhir *et al.*, 2016).

In summary, engineering assessments are useful frameworks to explore the differential impact of changes in technology components and production processes on overall technology cost, thereby helping identify specific policy drivers of cost reduction. But they need to be informed by assessments of how these inputs into the overall technology production cost change over time.

2.4 Combined Methods of Analysis

As highlighted when discussing engineering assessments' need for cost inputs from other methods, the three principal methods of cost estimation outlined above are not necessarily alternatives, and in fact combined approaches have considerable merit in producing more informed estimates of technology costs. Such assessments often include expert input, as in the Technology Innovation Needs Assessments (TINAs) undertaken for the UK government to identify cost reduction possibilities and drivers in a range of low-carbon technologies (LCICG, 2012a,b,c,d,e,f, 2013). For example, the offshore wind TINA (LCICG, 2012a) divides the turbines and their installation into components as part of a bottom-up engineering assessment model. It identifies significant potential savings in all major areas of construction and operation (turbines, foundations, collection and transmission, installation and O&M) based on discussions with experts. Though these expert inputs do not follow a formal elicitation approach, they nevertheless combine elements of different approaches discussed above.

Another example of combined cost assessment methods is the New Energy Externalities Developments for Sustainability (NEEDS) project, which assesses the future cost development prospects of a range of (predominantly low-carbon) energy technologies from the perspective of learning curves, bottom-up engineering assessments and a third category — what the study calls “long-term expert assessments” (NEEDS, 2006). The latter is a part commentary on the future applicability of learning curves, and part long-term expert elicitation, using primary research with technology experts. Junginger *et al.* (2010) present a detailed review of technology cost evolution possibilities for a range of

low-carbon energy technologies, taking into account not just past learning curve relationships (applied to different technology components) but also future innovation possibilities. These combined insights can add detail to the different drivers of future costs and build on the merits of each separate cost estimation approach. Nonetheless, there is still no firm basis on which to combine different methods of cost projection, with the emphasis to date having been on comparing results derived from different methods.

Having introduced and discussed each of the methods most commonly used to perform future technology cost estimates; the next section presents an overview of technology innovation systems frameworks, which more qualitatively explore the different dynamic processes involved in driving technologies through their innovation (and in many cases, cost-reduction) journey.

3 Frameworks to Describe Innovation Processes in Energy and Other Technology Sectors

3.1 Innovation as a Linear, Sequential Process from Invention to Commercialisation

Literature on technology innovation focuses on two central and highly interrelated questions — how technology costs reduce over time, and how new technologies become established in markets from the initial ideas that invent them. It can be considered that there are four successive stages of innovation: (1) basic research, (2) development to perfect a new technology; piloting leading to (3) full demonstration, and finally (4) commercial deployment of the technology through its adoption by the private sector (Fri, 2003). This model of innovation, called research, development, demonstration and deployment (RDD&D), has set the form for virtually all discussions on energy innovation (Fri, 2003). Furthermore, it has been argued that barriers to (socially optimal) innovation at any stage of this innovation chain could require policy interventions (Foxon, 2003; Gallagher *et al.*, 2006; Grubb, 2004; Jaffe *et al.*, 2005; Popp, 2010) as shown in Figure 2.

The 2007 Stern Review asserted that low-carbon energy technologies need both supply-push policies (such as those which help to foster research and development) and market-pull policies (such as those

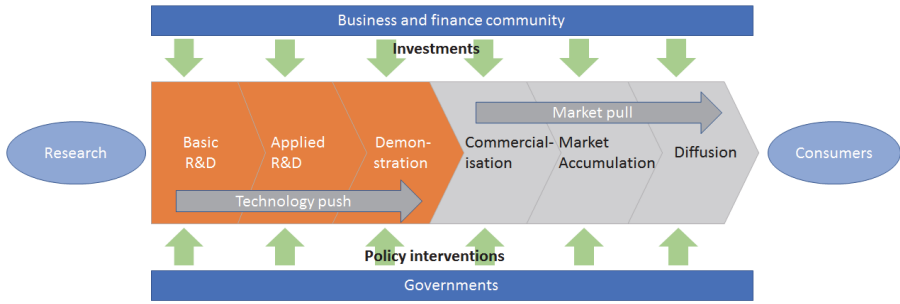


Figure 2: Illustration of the innovation chain.

Source: Reproduced from Grubb (2004).

which help create a market for these technologies, at a time when they are more expensive than their high-carbon equivalents). This requirement derives from market failures limiting private R&D (most importantly the positive spillovers which could be captured by free-riding firms) as well as missing markets for new, initially more expensive low-carbon energy technologies which, unlike many other innovations, tend to lack niche market opportunities, because energy is very often a purely homogenous good (Stern, 2007). In the latter case, policies such as feed-in-tariffs and tradeable renewables quotas (“green certificates”) had helped foster such niche markets at times when renewable energy was not cost-competitive (Ringel, 2006).

This qualitative conception of innovation does not identify the different degrees of policy support required at different stages of the innovation chain, and there is much disagreement over what the right balance should be. For example, in 2011 Policy Exchange, a prominent UK political think-tank, criticised the UK government’s drive to rapidly install offshore wind turbines through deployment subsidies to meet its 2020 renewable energy target (Policy Exchange, 2011). This critique is based on the claim that lessons that could reduce costs would not be learned at this speed of deployment (an increase in installed capacity from virtually zero in 2010 to almost 20 GW by 2020), and that in any case it is R&D rather than deployment which has been responsible for most of the cost reductions in offshore wind turbines to date given their level of immaturity, as asserted by Jamasb (2007). The critique may now look misguided, given the substantial reductions in offshore wind

power costs that have resulted from competition and learning, project finance and economies of scale that have arguably been made possible by such deployment subsidies (ORE Catapult, 2017). Indeed, offshore wind has confounded expectations in its transition from one of the most expensive to one of the cheapest low-carbon electricity generation technologies in recent years (Jansen *et al.*, 2020).

The high-profile announcements of the Global Apollo Programme initiative (King *et al.*, 2015) and the Mission Innovation initiative (Mission Innovation, 2015) during the 2015 Paris climate conference specifically targeted increased R&D support towards clean energy technologies. The Apollo programme drew criticism in light of its apparent refocus of innovation support away from deployment subsidies and towards R&D, with the assertion that technology innovation and cost reduction requires a careful balance of both of these drivers, which are in any case “symbiotic” (Radcliffe and Watson, 2015). Nevertheless, as an overall framework for consideration of drivers of technological innovation and cost reduction, the RDD&D framework is highly useful for conceiving of the processes behind technology costs reductions, and indeed is by far the most utilised system tool of those presented in this section for relating technology cost reductions to different processes and policy levers that incentivise or drive those processes.

Whereas the RDD&D framework says little about the process of — and scope for — technological improvement (and technology cost reduction) at different stages of technology maturity, the technology life-cycle model offers potentially important insights. Using this framework, Utterback (1996) assesses the forces governing the development of a range of technologies throughout the late 19th and 20th centuries, identifying a multi-phase evolution of both the products and the processes used to make these products, as shown in Figure 3.

In the first, “fluid” phase, rapid innovations occur as a number of competing products enter the market, testing the preferences of consumers towards different manifestations of a new technology (such as light bulbs with different types of filament, or typewriters with different types of keyboard format and carriage design). This fluid phase eventually gives way to a “transitional” phase in which a “dominant” design emerges, one which satisfies users as embodying what the product should be, and how it should perform. The transitional phase is dominated by major manufacturing process changes, as firms producing the dominant design

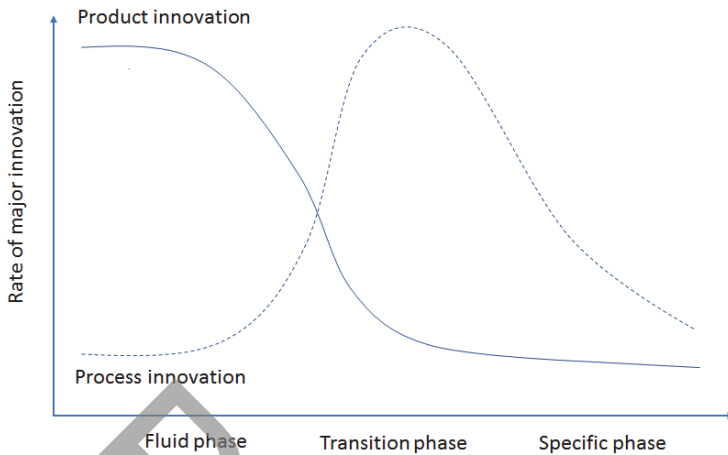


Figure 3: Different phases in the technology life-cycle model.

Source: Reproduced from Utterback (1996, p. 91).

compete on cost and quality. The final, “specific” phase, sees incremental innovations in the product and the use of capital-intensive, very specific manufacturing processes and firm structures, angled towards producing fairly standardised products at scale (Utterback, 1996).

The technology life-cycle model highlights at least two important factors relevant to innovation and cost reduction in low-carbon energy technologies. The first is that innovation may occur rapidly in the fluid phase but then become incremental in the transitional phase and less rapid altogether in the specific phase. It is therefore worth considering which phase a particular low-carbon energy technology is located in now, where it could be in the future, and what that means for future innovation potential, as well as whether this innovation will be radical or incremental. For example, Nemet (2009) analyses the development of the Californian wind industry, with a view to reconciling why the filing of highly cited patents rapidly declined just as the demand for wind power was taking off during the early 1980s. One explanation is that the opportunity for more radical (i.e., non-incremental) improvements to wind turbine technology declined as a dominant design (three-blade, upwind, horizontal axis turbines) emerged, and subsequent learning occurred through the deployment and use of the technology (Nemet, 2009).

Second, the technology life-cycle model distinguishes between innovation in products and processes, which suggests that these could be thought of separately, and which emphasises the possibility of innovation occurring in manufacturing rather than just in the design of the end product itself. As has been highlighted in previous research (Gambhir *et al.*, 2014), innovations and automation of many manufacturing processes played a key part in the cost reductions of crystalline silicon PV modules, whose fluid phase can be considered to have finished in the mid-1980s, followed by a long phase of manufacturing innovation and automation.

The technology life-cycle model thus provides potentially valuable insights into the different possibilities for innovation and cost reduction at different stages of low-carbon energy technology maturity, as well as the impact of specific policies (such as R&D and deployment support policies) within these different stages. In the early, fluid stages, more fundamental R&D support is likely to be more important in testing new design concepts and establishing some form of dominant design. Once this dominant design takes hold, innovation is more likely to occur through improvements to (and/or scale-up of) manufacturing processes, as well as more incremental product improvements resulting from lessons learned through manufacturing, deployment and operation in the field. During this transitional phase, there is, therefore, a potential benefit of market expansion through deployment support policies. Empirically, Jamasb's (2007) assessment of the relative impacts of R&D and deployment subsidies supports these assertions, with newer, "evolving" technology cost reductions more dependent on R&D than deployment subsidies, and "mature" technologies seeing the obverse. More recently, Elia *et al.*'s (2020) explicit assertion of the need to consider different technology maturity stages invokes (though does not directly cite) the lessons of the technology life-cycle model.

The RDD&D and technology life-cycle models both consider a somewhat linear, sequential nature of technology development, but in reality there is an ongoing interaction between different stages of a technology's evolution (Fri, 2003). In addition, there is evidence that policies affecting technology development and deployment interact with each other. For example, Freeman and Soete (1997) compare pairs of successful and unsuccessful innovations in each of the chemicals, scientific instruments and mechanical engineering industries, identifying the *interaction*

between R&D and sales and marketing as a key phenomenon across the different successful innovations. The authors assert that “one-sided emphasis on either R&D or sales does violence to the real complexity of the [innovation] process” (Freeman and Soete, 1997, pp. 216–217) — a notion reflected in Radcliffe and Watson’s (2015) criticism of the Apollo programme, as discussed above. It is therefore insightful to consider innovation not just in stages, but as part of a broader context of actors and institutions affecting technology development, as discussed in Section 3.2.

3.2 *Innovation as a Nonlinear Process*

One approach to more completely capturing the complex, nonlinear, picture of innovation comes from Technological Innovation Systems (TIS) analysis. Bergek *et al.* (2008) discuss the different features and functions of the TIS, which they define (quoting Carlsson and Stankiewicz, 1991, p. 111) as “network(s) of agents interacting in a specific technology area under a particular institutional infrastructure to generate, diffuse and utilize technology”. The TIS has three components (actors, networks and institutions) and seven functions (knowledge development and diffusion; influence on the direction of (re)search; entrepreneurial experimentation; market formation; resource mobilisation; legitimisation; and development of positive externalities), each of which has a role in diffusing the technology (Bergek *et al.*, 2008). It has been argued that this more systemic, as opposed to linear, framework to understand innovation is an improvement on linear frameworks such as those discussed in Section 3.1, since they show innovation as a collective activity consisting of many actors, with interactions between them (Gallagher *et al.*, 2012).

The TIS has to perform well across each of these functions to enable widespread penetration of a new technology, and there are a number of blocking mechanisms that could hinder the functioning of the TIS, such as poorly developed networks that limit knowledge spillovers, improvements in the performance of incumbent technologies in response to perceived threats from new technologies, and lobbying from incumbent organisations that fear losing out from the success of the new technology (Bergek *et al.*, 2008). For example, Figure 4 shows an energy TIS characterization of an early, experimental phase of German wind development in the late 1970s and early 1980s, with

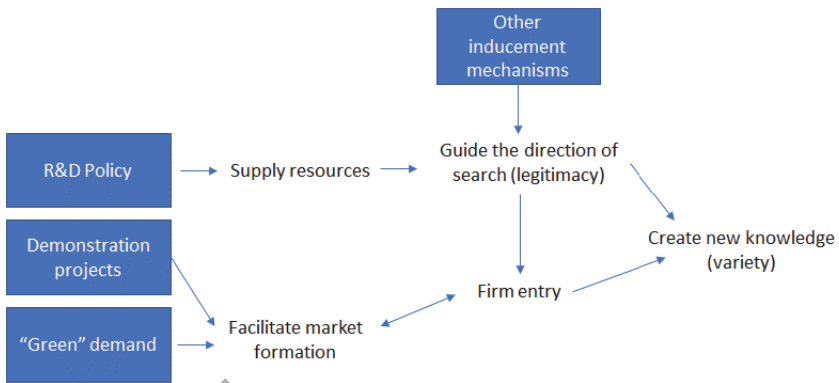


Figure 4: The TIS in the experimental phase of German wind development.
 Source: Reproduced from Bergek and Jacobsson (2003).

the focus on public policy (federal R&D support) helping to guide the direction of research, whilst at the same time demonstration projects, allied with a small but significant existing “green demand” (e.g., from environmentally aware farmers), helped to create an early market for the technology. This demonstrates on the one hand, the primacy of R&D policy in early technological development phases, but on the other, the requirement to also consider market creation as a further driver of knowledge creation and establishment of continuing and growing legitimacy for further technological development (Bergek and Jacobsson, 2003). The TIS thus helps fit specific actors to specific policy and other drivers of technological innovation and adoption.

It is arguably not difficult to fit these functions *post hoc* to the successful development of a particular technology. Nevertheless, the TIS is useful in identifying problematic areas which could hinder new technology development, deployment and cost reductions. For low-carbon technologies, the “legitimation” and “influence the direction of search” functions have been particularly challenging in the past, the former because new low-carbon technologies have provided an energy service at a greater cost (though with less environmental impact), and the latter because powerful interest lobbies such as centralised electricity utilities have sought to hinder the emergence of influence towards low-carbon technologies which are often decentralised (Bergek *et al.*, 2008).

Aside from the TIS framework, alternative contextual frameworks have been constructed to describe the development and deployment of new technologies. For example, the multi-level perspective (MLP) model describes how technologies (“artefacts”) break into niches which, if successful, begin to disrupt an existing technological regime, within the broader context of a socio-technical landscape (Geels, 2005; Geels and Schot, 2007). Such a model could be used to assess the prospects of particular low-carbon energy technologies, developed in niche markets within the context of a landscape increasingly reflective of environmental externalities, and with significant disruptive impacts on the existing regime, for example for electricity generation and transmission, whose regulatory and market arrangements may need to change to respond to increasing penetrations of intermittent or variable sources of generation (such as solar PV, wind, marine and tidal technologies).

Additionally, Winskel *et al.* (2013) have proposed a framework for setting out the factors that describe the technical evolution of different electricity generation technologies (Winskel *et al.*, 2013). This framework comprises a “learning pathways matrix” (LPM), a 2×2 matrix which on one axis distinguishes between radical and incremental periods of learning, and on another between the level of concentration or distribution of organisations (firms, governments, institutions) involved in the development of a design (or competing designs). For example, the government-led, concentrated effort to achieve radical innovation in first generation nuclear fission technology has given way to more incremental changes towards later generations, even though the effort has remained concentrated amongst relatively few organisations. By contrast, solar PV began in a similar status of radical innovation (using crystalline silicon) and concentration within national public programmes in the 1960s, then moved towards more incremental innovation in rooftop-mounted modules (with a high distribution of actors involved in their development and deployment) and utility-scale arrays (with the relative concentration of utilities driving this application) (Winskel *et al.*, 2013).

These frameworks (TIS, MLP, and Learning Pathways Matrix (LPM)) provide methods for identifying factors and agents important to the successful development and deployment of new technologies and the barriers hindering less successful technologies. There is now a considerable literature that uses the TIS (Gallagher *et al.*, 2012; Hekkert *et al.*, 2007; Jacobsson and Bergek, 2011; Jacobsson and Lauber, 2006)

and MLP (Cohen, 2010; Hodson and Marvin, 2010; Lauridsen and Jørgensen, 2010; Smith *et al.*, 2010; Späth and Rohracher, 2010) frameworks in particular to examine the success, failure or prospects for innovation in a range of energy technologies. It is important to note that these frameworks, and indeed all of those identified in this section, are NOT theories of technology cost reduction, but rather of innovation and penetration into socio-technical systems. Nevertheless, they are intimately connected to cost reduction, since this facet is a key driver of the widespread adoption of new technologies. As such it is essential to consider the extent to which they can inform methods of future technology cost estimates. Drawing on the language of the TIS, it is unlikely, for example, that deployment support policies will be successful in driving down the costs of a technology that has not yet become “legitimised” and to which there is widespread public opposition (and the reverse is also true).

One challenge of using the multiple insights from the innovation system frameworks remains how to link these to quantifiable rates of technological progress, expressed either in terms of technology performance improvements, technology cost reductions, or both. With a focus here on technology costs, and having reviewed the major frameworks of technology innovation, the next section aims to more explicitly link these two fields, by setting out the extent to which future technology cost estimates utilise insights from relevant technology innovation systems frameworks, the potential for improving their representation of innovation processes, and where possible quantifying the impacts of these processes. As argued below, this demonstrates that at this stage, future technology cost estimation practices lose much of the nuance gained around how technologies proceed along their innovation journeys, including the drivers and processes, as well as actors, that push them along these journeys. But they need not do so.

4 Links between Energy Technology Future Cost Estimation Methods and Innovation System Frameworks

Table 2 shows the potential insights from the key technology innovation systems frameworks discussed in the previous section, and specifically the extent to which they are commonly incorporated into the three

Table 2: Links between TIS frameworks and future cost estimation methods.

Commonly incorporated into energy technology future cost estimation method?				
Framework	Specific insight(s) on future costs	Learning curves	Engineering assessments	
RDD&D	Multiple drivers of innovation — including research & development, demonstration and deployment	Mostly — Multi-factor learning curves include deployment and R&D-related factors. Demonstration not commonly discussed or reflected, though potentially implicitly incorporated into R&D	Partially — Most commonly link future cost estimates to R&D funding but not to deployment levels, and with little or no mention of demonstration stage	Partially — In many cases key parameters driving cost reductions have been linked to R&D or deployment drivers
Technology life-cycle	Different phases of technology development	Partially — Learning curves sometimes split into different time periods, but in most cases these are not commonly linked to explicit discussion of technology life-cycle phases	No — Have not so far explicitly linked future cost estimates to the life-cycle phase of the technology	Partially — Have not commonly been used to explicitly link individual drivers of technology cost reduction to different phases of technology life-cycle
Technological Innovation Systems (TIS)	Multiple actors and factors in technology development and penetration into energy systems	Partially — Multiple factors such as R&D and deployment, linked to specific actors, have been incorporated into learning curves, but key TIS functions such as resource mobilisation, legitimisation; and development of positive externalities have not been	Partially — Expert elicitations haven't explicitly linked future cost estimates to considerations of market formation, resource mobilisation, legitimisation; and development of positive externalities. However, experts' mental models may do so	No — As with learning curves, multiple factors such as R&D and deployment have been discussed in the context of specific component cost reductions. But key parameters driving cost reductions have not been linked to different TIS functions

different energy technology future cost estimation methods. We focus here on three technology-specific frameworks (the RDD&D, technology life-cycle and TIS frameworks), at this stage setting aside less technology-specific frameworks such as the MLP and LPM also alluded to in Section 3. In the former (MLP) case, we deem this to have a central unit of analysis of whole technology systems, rather than specific technologies, whilst in the case of the latter (LPM), this framework is still relatively under-developed and conceptual.

It is important to note that there are exceptions to the general cases noted. For example, as noted in Section 3.2, some studies (Few *et al.*, 2018; Schmidt *et al.*, 2017) have explicitly taken into account non-R&D related factors into future technology costs, thereby accounting for more of the insights from the RDD&D framework. In addition, some analysis (Frontier Economics, Grantham Institute Imperial College London, 2015; Kittner *et al.*, 2017) using learning curves has taken into account the role of future R&D as well as deployment on future technology costs and applied this to two-factor (i.e. deployment and R&D) empirically derived learning curves, again thereby providing a fuller reflection of the RDD&D framework.

Table 2 can be summarised by noting that, whilst there are implicit links in future technology cost estimation methods to many of the factors and insights in the different innovation system frameworks, there is much more to be done to *explicitly* link future technology cost estimates to all of the drivers of innovation and cost reduction as noted in the RDD&D framework, to the specific life-cycle phases that the technology may or may not be in, or to specific functions in the TIS framework.

There are many ways in which insights from innovation system frameworks can be more readily brought to bear on the process of future technology cost estimates. First, Table 2 highlights that there is scope to include multiple variables and drivers of innovation and cost reduction that are commonly omitted from each future cost estimation method. For example, the TIS framework's functions of market formation; resource mobilisation; legitimisation; and development of positive externalities may all fall into a deployment-related element of the learning curve approach. Yet each of these functions could significantly influence the success with which deployment results in cost reductions. One only need consider solar PV's nadir period of the mid-2000s, when costs rose as a result of silicon production bottlenecks (a lack of the

TIS's "resource mobilisation") to realise the extent to which historically derived single- or multi-factor learning curves cannot reliably be used to predict near-term cost developments. Alternatively, if there is currently a significant scale-up of certain technologies and they are disrupting existing markets, as has been the case with lithium-ion batteries and their role in disrupting the internal combustion engine transport regime (Wesoff, 2016), then future R&D funding scenarios may bear more fruit in achieving cost reductions than without such scale-up, legitimisation or mobilisation of resources.

Secondly, implicit in this linking of commonly omitted variables that are present in the TIS to future cost estimation methods is a more in-depth and nuanced treatment of the different periods (and technology life-cycle phases) in which different levels of technology maturity are reached, and different forces that are critical in driving further development and cost reduction in each phase. This understanding is now more commonly being used to better understand the different phases of historical technology learning rates (as in, e.g., Smith *et al.*, 2016). Yet, it is still most commonly average learning rates that are projected forward to estimate future technology costs. A more complete discussion of the extent to which more mature technologies' future costs may more viably be estimated using more recent learning rates is likely to bear fruit in providing better-contextualised cost projections.

Thirdly, intricately linked to many of the drivers of innovation and cost reduction is the role of policy. As discussed in Section 2.3, the methods commonly employed to estimate future costs can be linked to specific policy drivers of cost reduction. Thus, learning curves incorporating deployed capacity and R&D funding levels are reflective of the potential efficacy of public policies to promote deployment and R&D. Expert elicitations that explore costs given different R&D funding scenarios can have explicit implications for required or desirable levels of R&D support policies. Engineering assessments can highlight which drivers of cost reduction (e.g., technical performance improvements, production scale) are most important, lending insights into the policies that could be most effective in achieving these cost reductions. Detailed consideration of policy implications in this way helps to shed light on the debate of the relative merits of R&D versus deployment support policies which, as discussed in Section 2.1, continues to be a critical and much-contested area of research, but which requires further consideration

(Anadón *et al.*, 2017; Grubb *et al.*, 2021). Particularly if it leads to a more nuanced discussion of public R&D versus the private R&D induced by profitable deployment, this would help to build on the relatively limited, though increasing, number of analyses explicitly exploring the balance between these drivers on future energy technology cost reductions (Few *et al.*, 2018; Frontier Economics, Grantham Institute Imperial College London, 2015; Gambhir *et al.*, 2016; Kavlak *et al.*, 2018; Kittner *et al.*, 2017; Nemet and Baker, 2009; Schmidt *et al.*, 2017).

To demonstrate the potential benefits of more closely linking innovation framework insights to energy technology cost projections, we review the performance of a sample of past cost projections against actual cost developments for two energy technologies (offshore wind and nuclear) and observe how such projections accounted for energy TIS functions, if at all.

For offshore wind, as shown in Figure 5, the actual cost reduced faster since 2014 than foreseen by three different cost projection methods. The offshore wind sector has seen a well-functioning TIS in many of the Northern European countries deploying it at scale. In the UK, TIS functions including market formation (through deployment support in the form of guaranteed minimum or fixed price offtakes), knowledge development and diffusion and entrepreneurial experimentation (through the R&D and learning in successive vintages of turbine manufacture, each with increasing size) have all been central to its cost reduction journey (Jennings *et al.*, 2020). Critically in the UK, another TIS function, that of influencing the direction of search, has been prominent since a decade ago, when the UK Department of Energy and Climate Change’s 2011 Renewable Energy Roadmap made explicit a requirement for costs to fall through developing a supply chain, innovating and minimising investment risk (DECC, 2011) — each of which was achieved in the ensuing decade.

Similar processes were at play in Germany and Denmark. In the former, by the start of the 2010s, a generous Feed-in-Tariff for offshore wind and the successful launch of a large test field project (Alpha Ventus) constituted a tipping point in the industry, leading to substantial sectoral growth and associated industry scale (Reichardt *et al.*, 2016). In Denmark’s case, the industry was supported by a consistent and long-term innovation system, including a high degree of R&D linking universities to turbine and windfarm developers, deployment support,

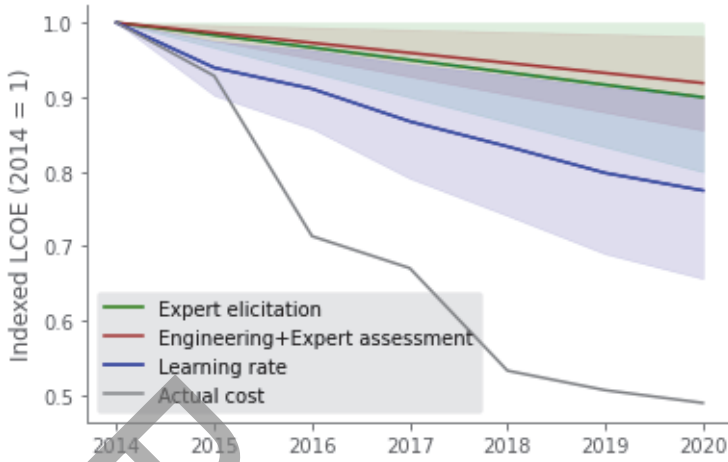


Figure 5: Offshore wind levelized cost of electricity (LCOE) development from 2014 using three future cost estimation methods, and actual cost development since 2014.

Notes: Expert elicitation median (green line) and low-to-high range (green plume) for global values, from Wisner *et al.* (2016); Engineering + Expert assessment mean (brown line) and low-to-high range (brown plume) for UK values, from LCICG (2012a); learning rate mean (blue line) and low-to-high range (blue plume) from Rubin *et al.* (2015), combined with global actual deployment data from Froese (2019) and IEA (2021); Actual cost (grey line) refers to global unsubsidised cost from Lazard data as cited in Wisner *et al.* (2021). Full calculations and source details in Supplementary Data.

as well as public support for the technology (Wieczorek *et al.*, 2015). Indeed, reflecting on the pervasive underestimates of both onshore and offshore wind cost reductions in their 2015 expert elicitation, Wisner *et al.* (2021) suggest that experts may have under-predicted downward cost pressures from auctions and competitive procurement, themselves driving increasing demand and leading to further industrialisation and industry maturation, with rapidly increasing turbine sizes. Each of these processes speaks to an intensive and virtuous cycle of market formation and entrepreneurial experimentation (two core TIS functions) that was underestimated by the experts.

As a contrast to offshore wind, nuclear power costs actually increased over the past decade, and at a faster rate than foreseen by any of the cost projection methods shown (Figure 6). Reasons include their tendency to be “megaprojects” subject to cost overruns (Sovacool *et al.*, 2014), lack of design standardisation, along with increases in reactor scale and

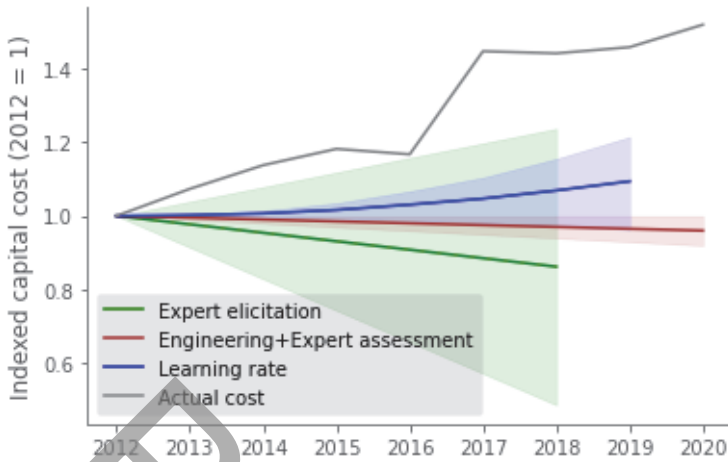


Figure 6: Nuclear overnight capital cost development from 2012 using three future cost estimation methods, and actual cost development since 2014.

Notes: Expert elicitation median (green line) and low-to-high range (green plume) for US values, from Abdulla *et al.* (2013); Engineering + Expert assessment mean (brown line) and low-to-high range (brown plume) for UK values, from LCIC/G (2013); Learning rate mean (blue line) and low-to-high range (blue plume) from Rubin *et al.* (2015) and Grubler (2010), combined with actual global deployment data from IEA (2020); Actual cost (grey line) refers to global unsubsidised costs from Lazard (2020) and previous Lazard cost estimates. Full calculations and source details in Supplementary Data.

complexity and fragmentation in industry structure and plant ownership (Eash-Gates *et al.*, 2020). Markard *et al.* (2020) explicitly use the TIS framework to identify a number of failures, including an eroding actor base, shrinking opportunities in liberalized electricity markets, the break-up of existing networks, loss of legitimacy, increasing cost and time overruns and abandoned projects. They assert that recent and future investments in new nuclear might suffer from the diseconomies of a declining industry, in which industrial competencies become increasingly scarce and concentrated.

Tables 3 and 4 set out the factors used in each of the cost projection methods shown in Figures 5 and 6 respectively, highlighting the extent to which the insights from energy TIS analysis were brought to bear on these cost projections. In both technology cases, there was little recourse to the detailed elements of the TIS in either the expert elicitations or combined assessments, whilst the (single factor) learning curve

Table 3: TIS factors accounted for in offshore wind future cost estimation methods.

Method	TIS factors accounted for
Learning curve extrapolation (using learning rates from Rubin <i>et al.</i> , 2015)	None explicitly, though a single factor learning curve accounts for deployment-related factors (e.g. learning-by-doing, industry scale) implicitly
Expert elicitation (Wiser <i>et al.</i> , 2016)	Focus on technical parameters only (CapEx, OpEx, Capacity Factor, Project Life, Cost of Capital). Explicitly avoids asking for projections conditional on R&D, policy, deployment, or other factors. However, analysed cost estimates by expert type and noted that those claiming expertise in wind energy markets and/or cost analysis were more optimistic than those who claimed expertise in systems or sub-systems
Combined (Engineering + Expert assessment) (LCICG, 2012a)	Explicitly discusses the role of public sector intervention to address demand uncertainty, shared testing and infrastructure, positive externalities of Private R&D and data-sharing. Also notes limited competition in some areas. However, cost reduction focused primarily on R&D-based innovation in individual system components, with only limited discussion of and role for market size expansion and learning by doing in deployment. Explicitly excludes consideration of planning, supply chain, related infrastructure and finance

extrapolations by definition only account for the cumulative deployment of each technology.

In essence, different technologies' cost-reduction prospects will be highly influenced by the technological innovation system surrounding them. Each of the innovation system frameworks discussed can offer insights into the causality between research, market, regulatory, or other conditions which are likely to prove highly influential in determining future technology costs.

There is preliminary evidence that such consideration of a broader range of evidence around innovation could bear fruit: Savage *et al.*

Table 4: TIS factors accounted for in nuclear future cost estimation methods.

Method	TIS factors accounted for
Learning curve extrapolation (using learning rates from Rubin <i>et al.</i> (2015) and Grubler, 2010)	None explicitly, though a single factor learning curve accounts for deployment-related factors (e.g., learning-by-doing, industry scale) implicitly
Expert elicitation (Abdulla <i>et al.</i> , 2013)	Specified to experts that the plants were built under a “favorable” regulatory environment. Acknowledges that future costs of newer nuclear technologies (Small Modular Reactors) are dependent on a range of factors including national and international markets. However, results reported in Figure 6 are for then-current generation Gigawatt scale nuclear reactors
Combined (Engineering + Expert assessment) (LCICG, 2013)	Accounts for learning by doing and learning by R&D. Case for public intervention identified on the basis of the high barriers to entry, the lack of competition and the stringency of regulatory requirements. Explicitly notes the importance of public acceptance, potential cost increases and the importance of international partnerships

(2021) recently tested 133 participants’ responses on a range of questions regarding current and future aspects of electric and autonomous vehicles. A treatment group that was explicitly asked to consider policy, economic and social factors of potential relevance provided a wider range of forecast values, and also demonstrated less overconfidence in assessments of current values than a group who did not receive this treatment. This suggests that including a consideration of many more factors into expert elicitations could help reduce overconfidence in technology cost projections derived from them. It stands to reason that structuring the presentation and discussion of these factors within an established innovation systems framework such as the TIS could further improve this practice. The same should be true of engineering assessments informed by experts, and wider use of innovation systems frameworks could also help in contextualising learning curve extrapolation-based projections. The challenge is to quantitatively incorporate these insights

so that we can understand, if not necessarily how much technologies will cost in the future, then as a minimum what different policy, market and investment scenarios will mean for their cost reduction trajectories.

5 Conclusions and Policy Implications

Energy technology future cost estimates are central to determining how expensive it will be to address the climate change challenge. There are a number of established methods to produce such estimates: extrapolating learning curves based on past experience; asking experts; and analysing detailed, component and manufacturing process models of the technologies, as well as combinations of these methods. At the same time, there are a number of detailed technology innovation systems frameworks which describe the processes and actors behind innovation and market penetration for low-carbon energy technologies, which are key to helping understand the degree to which their cost can reduce. These include experimentation and the arrival at design dominance, standardisation and repeated manufacture of designs once markets are formed, the legitimisation of those designs as they break into and disrupt existing technological regimes, and the development of positive externalities as technologies become embedded in energy systems, realising complementarities with other technologies and networks. These innovation systems frameworks also give a central role to policies, whether supply-push in the form of R&D support, or demand-pull in the form of subsidies, procurement, or contracts and tariffs to guarantee future revenues, to support market formation and expansion. Yet — whilst there are several examples of links between energy technology cost estimation methods and technology innovation systems frameworks — much more could be done to make these links more explicit.

As discussed in this paper, there are numerous ways in which this could be done. For example, rather than pure extrapolation of empirically established learning curves, future learning rates might not only be calculated on the basis of future deployment levels and future R&D funding levels, but might also account for the level of maturity of the technology, its stage in the technology life cycle, the degree of legitimisation of the technology or the degree to which it has begun to disrupt an existing market. Similarly, expert elicitations should be conducted with

a view to fully discussing not only the technology, but its surrounding innovation system, and the extent to which the different actors and functions driving innovation, cost-reduction and commercialisation are operating effectively or otherwise. Engineering assessments and combined methods should include a more explicit understanding of whether component cost reductions and performance improvements are likely within the existing and possible future contexts of the TIS. And those making projections should frequently compare them to actual data as it becomes available, to learn how their projections are performing and why.

This paper acknowledges that such efforts have begun. It gives a number of examples of how the boundaries of future technology cost estimation are being pushed in order to more explicitly link the key factors which are likely to drive cost reductions to the actors and processes of innovation, as highlighted by technology innovation systems frameworks. More widespread incorporation of such factors, with quantification where possible, would add insight and nuance to future energy technology cost estimates, highlighting contingencies, drivers and sources of uncertainty. Critically, it would also help to more closely link specific policies to the factors that are most likely to influence these future costs.

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