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A report for UKERC by
UKERC Technology & Policy Assessment Function



Presenting the Future

An assessment of future costs estimation methodologies in the electricity generation sector

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Preface

This report was produced by the UK Energy Research Centre's (UKERC) Technology and Policy Assessment (TPA) function.

The TPA was set up to inform decision-making processes and address key controversies in the energy field. It aims to provide authoritative and accessible reports that set very high standards for rigour and transparency. The subject of this report was chosen after extensive consultation with energy sector stakeholders and upon the recommendation of the TPA Advisory Group, which is comprised of independent experts from government, academia and the private sector.

The primary objective of the TPA, reflected in this report, is to provide a thorough review of the current state of knowledge. New research, such as modelling or primary data gathering may be carried out when essential. It also aims to explain its findings in a way that is accessible to non-technical readers and is useful to policymakers.

The TPA uses protocols based upon best practice in evidence-based policy, and UKERC undertook systematic and targeted searches for reports and papers related to this report's key question. Experts and stakeholders were invited to comment and contribute through an expert group. The project scoping note and related materials are available from the UKERC website, together with more details about the TPA and UKERC.

About UKERC

The UK Energy Research Centre is the focal point for UK research on sustainable energy. It takes a whole systems approach to energy research, drawing on engineering, economics and the physical, environmental and social sciences.

The Centre's role is to promote cohesion within the overall UK energy research effort. It acts as a bridge between the UK energy research community and the wider world, including business, policymakers and the international energy research community and is the centrepiece of the Research Councils Energy Programme.

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Executive Summary

Introduction

Since the mid-2000s, fossil fuel price increases have contributed to considerable increases in wholesale and consumer prices for electricity in the UK. Other commodity price rises, supply chain constraints, market dynamics and a range of other factors have increased construction costs in both renewable energy and gas-fired developments. As we look to the future, estimates of the costs of building new nuclear and carbon capture and storage plants in the UK have also increased.

Whilst fuel prices have always been volatile, many of the increases in costs and prices were not anticipated and stand in sharp contrast to a widely shared view that costs tend to fall over time, particularly for emerging technologies. A substantial literature indicates that innovation in the form of 'technological learning' reduces costs and that policy supporting the deployment of technologies helps this learning to occur. Yet it is clear that learning effects may not always emerge as anticipated, and/or can be overwhelmed by other factors.

The importance of accurate generation cost projections has increased as a result of the government's proposals for Electricity Market Reform (EMR), which will shift key aspects of power sector investment choices away from private companies and back towards the government, for example through the setting of current and future strike prices for different technologies. It is now even more important for policy makers to understand the strengths and weaknesses of cost estimates and forecasts.

This report considers the role and importance of electricity cost estimates and the methodologies employed to forecast future costs. It examines the conceptual and empirical basis for the expectation that costs will reduce over time, explains the main cost forecasting methodologies, and analyses their strengths, limitations and difficulties. It considers six case study technologies in order to derive both technology specific and generic conclusions about the tools and techniques used to project future electricity generation costs.

Learning rates and engineering assessment

There is a rich and evolving international literature on the sources of cost reduction in all technologies, and how best to estimate future cost-trends. The principal approaches can be characterised as 'engineering assessment', including parametric modelling, and the use of 'learning' or 'experience' curves. The two approaches are complementary and offer different sources of insight, as well as different limitations and potential for error.

Engineering-based approaches offer advantages for early stage technologies with very limited market exposure, since the absence of historical cost and deployment data militates against the use of experience curves. The potential to consider sources of cost reduction 'parametrically' – that is to break down the costs of a technology into a set of component parameters – also allows for sensitivity to key cost changes to be assessed. Engineering assessments may also help the analyst to identify discontinuities or innovations that learning curves cannot anticipate.

Learning curves chart the relationship between market growth and cost reduction, an empirical phenomenon that has been identified in numerous technologies and sectors of the economy. The literature both applies learning curves to particular technologies and discusses their usefulness and limitations. The complexities associated with learning curves include: whether learning rates vary through time and as technologies mature; the presence of 'cost floors'; the difficulties associated with projecting deployment; divergent costs and prices; system boundary issues; alternative sources of learning (such as learning by researching).

Analysts are seeking to improve the predictive value of learning curve analysis and interrogating the other factors that drive cost reduction. Understanding of learning as a phenomenon is becoming more sophisticated. The literature pays considerably less attention to the

Perhaps the key challenge is in representing and communicating uncertainty – what is known, not known and unsure in an uncertain world – to decision-makers seeking certainty.

methodological issues associated with engineering assessment, but does not challenge its usefulness.

Overall, it is clear that engineering and learning/market-based approaches are best seen as partners in the quest to better understand cost reduction potential. Both offer valuable insights, but their limitations need to be properly appreciated by users and by those making decisions based upon the analysis that uses them.

Understanding cost trends better: the technology case studies

A wide range of factors affect cost and price changes. These are additional to the limitations of learning/engineering-based techniques for assessing cost reduction potential. The report investigates these through a set of six case studies: onshore wind, offshore wind, nuclear, carbon capture and storage (CCS), combined cycle gas turbine (CCGT) and solar photovoltaics (PV).

The case studies reveal a widely divergent picture of cost trends between the principal technologies reviewed for this report. The trend for PV has been most resolutely downward, albeit from the highest base. Wind technologies and CCGT have also seen consistent and substantial cost reductions, although the cost of both turned upwards, for different reasons, during the mid and late 2000s. The offshore wind case study provides a variety of insights both methodological and empirical. In this instance exogenous factors over-rode learning, but the potential for learning in the early stages was also overstated and factors endogenous to the roll out (such as moving to deeper water) were not always fully factored into early cost projections. The literature on nuclear provides a great deal of insight into why costs have tended to rise rather than fall, at least in the European and US context. Analysis of CCS costs remains largely theoretical at the time of writing, though the literature demonstrates increasing attention to detailed plant design and a trend towards costs rising as detail increases.

One size does not fit all. Technology specifics are paramount to cost reduction prospects. Forecasters need to be alert to the specific characteristics and thematic distinctions of the different technologies and their particular physical, commercial, and regulatory environments. For this reason the use of 'proxy' learning imported from other sectors (even similar ones) needs to be treated with caution. The review also suggests that technologies which are modular, have scope for mass production, and have scope for technological innovation, are more likely to achieve on-going cost reductions. Technologies which are inherently complex, need to realise significant project-level economies and require substantial complex regulation, will find cost reductions more difficult to realise.

Overarching conclusions

The review shows that the cost of electricity generation can fall through time and as deployment rises. The review revealed considerable empirical evidence of cost reduction, in many technologies. It also revealed a detailed and sophisticated discourse related to the use of learning curves.

Fuel and commodity prices can have large impacts. Largely unanticipated by most costs forecasters, escalations in the prices of both fuels and essential raw materials contributed greatly to disparities between cost projections and outcomes during the 2000s. These overwhelmed downward cost trends previously seen in several technologies and anticipated in others.

In the short-term costs may rise before they can fall. Cost reductions from learning can be overwhelmed in the short-term by supply chain bottlenecks, build delays and 'teething trouble', for example lower than expected reliability at first. There is historical precedent for technologies deployed in the power sector to demonstrate cost increases during early commercialisation before supply chains and learning from experience are firmly established.

Market growth is a necessary but not sufficient condition for learning and cost reduction. The review reveals the multi-dimensional nature of both projecting future costs and creating the conditions for costs to fall. The literature highlights the learning potential of spill-overs from research, indicating that continued attention to RD&D is an essential accompaniment to market enablement. Regulatory constraints also need to be addressed and policy may also be able to facilitate cost reduction through supporting the skills base and ensuring effective sequencing of projects.

It is important to acknowledge and communicate the assumptions and uncertainty inherent to cost projections. Cost reduction projections are difficult and challenging, so analysts and policy makers should not be surprised if forecasts turn out to be wrong. However, projections do need to make uncertainties and assumptions clear. In particular there is a need to make a distinction between different types of uncertainty, and recognise that some categories of uncertainties cannot be resolved:

- ***Some of the uncertainties revealed by the case studies are exogenous, inherently unpredictable and may exhibit high volatility.*** These risks are difficult to anticipate, quantify and predict rather than being impossible to imagine. They are 'known unknowns' and may be investigated and mitigated by the use of numerical ranges and scenario analysis. However, some 'sideswipes' may be inevitable, and can overwhelm cost projections even in the best of analytical worlds, albeit perhaps temporarily.
- ***Other cost drivers are endogenous, more 'known' and therefore lend themselves more readily to future projection.*** It is, for example, reasonable to expect cost reductions over time to accrue from returns to adoption such as learning effects, ongoing innovation, scale effects, and standardisation. It is also possible to anticipate and manage factors such as short-term bottlenecks and supply chain constraints. This has important implications for policy design such as time horizons and sequencing.

Despite uncertainties, recent studies of energy technology costs show improved 'appraisal realism'. The scope of cost estimates (for example what is and what is not included) and the assumptions regarding other key variables (such as the discount rate) tend to be well documented in recent analyses. Many recent studies explicitly take account of a variety of factors able to drive costs in the wrong direction. Nonetheless, many contemporary forecasts anticipate a return to cost reductions over the forthcoming years and decades even where costs/estimates of costs have risen. In part this reflects an expectation that factors such as supply chain constraints will ease and underlying learning effects will lead to cost reduction through capital cost reduction and efficiency/performance improvement.

Overall, this review reveals a large dataset on technology costs (past, present and future) and a rich and complex literature that discusses the factors that affect cost trends over time. Our understanding of cost reduction forecasting is undoubtedly improving with time, in part through learning from recent significant failures to anticipate changes to cost trends.

We know with confidence that costs can fall, and that given the right conditions 'learning' can make this happen. The role of policy in driving cost reduction is very apparent in several of the case studies. However, it is less straightforward to be confident about the extent to which costs will fall in a particular period in time, and policy can have multiple impacts, for example regulatory complexity can also militate against cost reduction. Cost reduction projections are difficult and challenging and often proved wrong.

Perhaps the key challenge is in representing and communicating uncertainty – what is known, not known and unsure in an uncertain world – to decision-makers seeking certainty.

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List of abbreviations and acronyms

AACE	Association for the Advancement of Cost Engineering
BAT	Best Available Technology
BERR	(Department of) Business Enterprise and Regulatory Reform
BIPV	Building Integrated PV
BOS	Balance Of System
CCC	Committee on Climate Change
CCGT	Combined Cycle Gas Turbine
CCS	Carbon Capture and Storage
CdTe	Cadmium Telluride
CfD	Contract for Difference
CO_2	Carbon Dioxide
CO_2e	Carbon Dioxide equivalent
c-Si	Crystalline Silicon
DECC	Department of Energy and Climate Change
DTI	Department of Trade and Industry
EDF	Electricite de France
EMR	Electricity Market Reform
EPR	European Pressurised Reactor
EU	European Union
ETS	EU Emissions Trading Scheme
EWP	Energy White Paper
FEED	Front-End Engineering and Design
FGD	Flue Gas Desulphurisation
FiT	Feed-in Tariff
FOAK	First Of A Kind
GBP	British Pounds (£)
GDP	Gross Domestic Product
GW	Gigawatt
IEA	International Energy Agency
IGCC	Integrated Gasification Combined Cycle
kg	Kilogram
kW	Kilowatt
kWh	Kilowatt hour
LCOE	Levelised Cost Of Energy
LNG	Liquefied Natural Gas
LWR	Light Water Reactor
MFEC	Multi Factor Experience Curve
MW	Megawatt
MWh	Megawatt hour
NEA	Nuclear Energy Agency
NOAK	Nth Of A Kind
O&M	Operations and Maintenance
OECD	Organisation for Economic Cooperation and Development
PIU	Performance and Innovation Unit
PTC	Production Tax Credit
PV	Photovoltaics
PWR	Pressurised Water Reactor
R&D	Research and Development
RO	Renewables Obligation
RPI	Retail Price Index
SCR	Selective Catalytic Reduction
SFEC	Single Factor Experience Curve
TFEC	Two Factor Experience Curve
TPA	Technology and Policy Assessment (a function of the UKERC)
UK	United Kingdom
US	United States of America
UKERC	UK Energy Research Centre
Wp	Watt peak

1. Introduction – Context, relevance and approach to this report

1

Context

In Britain both the price of electricity and the projected costs of electricity production from new power stations have been subject to increases and volatility in recent years. Since the mid-2000s, fossil fuel price increases have led to considerable increases in the wholesale and consumer prices for electricity in the UK and in many other countries. Whilst in the period since 2008 gas and power prices have fallen again in the US as a result of shale gas expansion, prices have risen in European and Asian markets (DECC 2012c, Johnsson and Chediak 2012, Bolton 2013, IEA 2013). In addition in recent years a range of factors including commodity price rises, supply chain constraints and market dynamics have increased the construction costs of many types of power station (Greenacre *et al.* 2010, IEA 2010a, Mott MacDonald 2010). Chapter 2 reviews recent estimates of costs.

Whilst fuel prices have always been volatile, many of these cost increases stand in sharp contrast to a widely shared view that costs tend to fall over time, particularly for emerging technologies (IEA 2000, Greenacre *et al.* 2010). Many energy system scenarios are predicated on innovation and 'learning effects' that lead to cost reductions as new technologies are developed and deployed. Historically, this aligns well with experience; cost reductions over time for most technologies are well documented. Yet the recent gap between expectation and reality gives rise to important questions about how and why costs rose when they were expected to fall and how confident we can be in analyses that continue to predict cost reductions over time. This has particular relevance at a time when many of the UK's older power stations are scheduled to close and the government has ambitious plans to decarbonise the electricity sector. The future costs of new nuclear, renewable energy and fossil fired plants with and without carbon capture are of fundamental importance to policymakers and investors alike.

This report

This report considers the role and importance of cost estimates for energy policy and the electricity generation industry and the methodologies employed to forecast future costs. It examines the theoretical reasons behind the expectation that costs will reduce over time, explains the processes and mechanisms that underpin the main cost forecasting methodologies, and analyses the strengths, limitations and difficulties with the techniques used to make judgements about cost reductions over time.

In order to analyse further the accuracy of cost forecasting and the robustness of the forecasting methodologies, the report draws upon six case studies, produced by UKERC to support this report, each of which focuses on a different generating technology. The case study working papers are available on the UKERC website (www.ukerc.ac.uk)[1]. Each case study compares past expectations of cost trajectories with actual out-turns and changes in cost estimates over time and analyses the main drivers of cost increases or decreases.

These drivers vary in character – some being quite technology-specific, others more policy-oriented or micro- or macro-economic in nature. They comprise a heterogeneous assortment of forces that impinge on costs trajectories and/or on the estimation and forecasting of costs, and we have chosen to refer to them as 'themes'. In Chapters 4 and 5 we distinguish between themes of a 'methodological', 'endogenous' and 'exogenous' nature.

Relevance

Power generation costs and cost forecast methodologies are of considerable importance for several reasons. The range of stakeholders and interested parties is wide and the discourse around costs of considerable public and political interest. Costs and cost forecasting are important to the utilities, policy makers, investors, the academic community, and of course, electricity consumers.

In addition, the issue of power generation costs – in particular the evolution of costs for different technologies and the anticipated outlook for those costs in the future – is of fundamental importance to strategies for reducing emissions of the pollutant gases responsible for climate change. For example, the models used in the Stern Review (2006) and in scenario modelling exercises such as UKERC's 2050 Energy Project (Anandarajah *et al.* 2009), rely upon numerous judgements about the future costs of energy technologies. These scenarios suggest that the transition to low-carbon energy systems will feature decarbonisation of the electricity generation sector to a very great degree, first because it currently accounts for a significant share of carbon emissions, and second because electrification of heat and transport is expected to help to provide a cost effective means to decarbonise these sectors (CCC 2010). It is difficult to envisage a decarbonised energy system that does not include a substantial move to low carbon sources of electricity. However, the scale of expansion of nuclear power, renewable energy and carbon capture and storage in many modelling exercises is in large part predicated on the expectation that their costs will fall over time. If the judgements made about cost reductions prove to be wrong, the role of power generation may become less prominent and/or it may prove to be more expensive to reduce greenhouse gas emissions.

In the shorter term, the UK has committed to meeting 15% of its final energy consumption from renewable sources by 2020 in order to comply with the EU Renewables Directive (EC 2009). Again, the choice of technologies to meet the target are influenced by cost projections (Greenacre *et al.* 2010). Finally, the role and accuracy of generation cost

[1] *www.ukerc.ac.uk/support/tiki-index.php?page_ref_id=2863*

projections has increased in policy importance as a result of the government's proposals for Electricity Market Reform (EMR) (HM Government 2012). EMR will shift key aspects of power sector investment choices away from private companies and back towards the government. Government will be responsible for setting Contracts for Difference strike prices and determining the level of capacity desired through the Capacity Mechanism (Ibid.), and have recently published their proposed strike prices for a range of renewable generation technologies (DECC 2013a). It is now even more important for policy makers to understand the strengths and weaknesses of cost estimates and forecasts. With long lead times associated with building plants such as nuclear power stations, long lives of many of the assets in question and the long-term nature of the choices made now all increase the importance of cost estimation methodologies that are robust and trustworthy. This report examines the extent to which they are.

1.1 Methodology

1.1.1 TPA approach

The report is authored by analysts at Imperial College working for the Technology and Policy Assessment (TPA) function of the UK Energy Research Centre (UKERC). The TPA function was set up to address key issues and controversies in the energy field and aims to provide authoritative inputs to decision-making processes in this arena, using an approach which learns from the practice of systematic review. This aspires to provide a more convincing evidence base for policymakers and practitioners, avoid duplication of research, encourage higher research standards and identify research gaps. This evidence-based approach is common in areas such as education, criminal justice and healthcare. UKERC's TPA function has developed an approach that suits energy policy questions (Sorrell 2007).

The goal is to achieve high standards of rigour and transparency. However, energy policy gives rise to a number of difficulties for prospective systematic review practitioners and the approach is not common in energy. We have therefore set up a process that is inspired by the evidence-based approach, but that is not bound to any narrowly defined method or techniques (Ibid.)[2].

1.1.2 Assessment sequence

This assessment follows a generalised approach developed for all TPA work. The TPA has identified a series of steps that need to be undertaken in each of its assessments. These steps, derived from the practice of systematic review in non-energy policy analysis, give rise to the process for this study, outlined in Figure 1.1 below.

Figure 1.1: Typical process for TPA studies

	Scoping prospective issues	Solicit expert input	Define criteria for assessment	Review literature	Synthesis and analysis	Prepare draft report	Consult, peer review and refine	Publish and promote
Questions/issues	What are key problems and issues	Need to reflect a range of informed opinion	Ensure transparent, rigorous and replicable process	Need to review literature thoroughly	Need to apply rigorous criteria to evaluation of relevant studies	Need to identify key issues and discuss initial findings with stakeholders	Need to seek peer review and gain wide ranging criticism of initial work	Need to ensure report reaches key audience
Actions	Write scoping note Seek feedback from advisory group Seek feedback from online listing of initial scoping	Appoint expert group Hold expert/ stakeholder workshop	Develop assessment protocols Discuss expert group and AG Place protocols in public domain	Apply protocol to literature search Detailed and transparent 'trawl' Identify relevant sources	Apply protocol to evaluation and synthesis of literature Detailed and transparent assessment of evidence base	Write preliminary draft assessment	Host stakeholder workshop to discuss draft report Send draft report for peer review Make appropriate revisions to draft report	Design and graphics Publication Launch events
Outputs	Scoping note	Web publication of expert group	Assessment protocols			Draft report	Final report	Published report

[2] See also 'About the TPA' at www.ukerc.ac.uk/support/TPABackground&structure=TPA+Overview

1.1.3 Systematic review and expert elicitation

The evidence and data used in this report are sourced from a targeted review of the academic and 'grey' literature most directly relevant to the subject matter of each chapter (and of each case study in the case of Chapter 4). The evidence and data for Chapter 3, which focuses on forecast methodologies, was sourced from a systematic search of the available academic literature. In addition, the project team consulted with an expert group convened to help with the research and review the draft report. See Annex for details of the expert group members.

The systematic review for Chapter 3 started with a set of key words that provided the basis for the creation of specific search strings using Boolean terminology. The challenge was to keep the number of search strings to a manageable level without losing relevant papers from the review process. The project team therefore selected those combinations of terms deemed to provide the appropriate coverage and the systematic search revealed approximately 1,150 evidence hits. However, over 400 of these were duplicates across the databases and removal of these reduced the results total to under 750. This number was then further reduced to approximately 450 by removal of any hits that, judging from their title or abstract, were immediately obvious as being of little or no relevance. The remaining total was further reduced via a process of closer inspection to approximately 200 pieces of evidence that were then rated for relevance (see Annex for definition). In the writing of Chapter 3, the majority of the evidence used is rated 1 or 2 with only very limited contextual use made of evidence rated 3 and 4.

The approach to the technology case studies was to conduct a targeted systematic review of the evidence base for the cost trajectories of each technology. Across the six case studies, the project team collated over two and half thousand data points and a detailed analysis of this data can be found in the working papers referred to above[3].

1.2 Report structure

The structure of this report is as follows:

- **Chapter 2** examines the importance and differing roles of cost estimates, forecasts and analysis in the electricity generation industry. It examines why and how costs matter, in particular with reference to government policy making, before going on to investigate their various forms and specific uses.
- **Chapter 3** considers the reasons the cost of a product or process is expected to go down over time and then goes on to examine experience curves and engineering assessment, the principal methodologies used to make forecasts and projections of future costs in power generation. The chapter considers the strengths, limitations, caveats and refinements of each approach.
- **Chapter 4** summarises and discusses the findings of six case-studies which examine cost estimates and future costs forecasts of different electricity generation technologies. The chapter examines what these case-studies tell us about past expectations of future cost trajectories and the drivers that have contributed to the shape of the technologies' projected and actual cost trajectories. The six technologies examined are: combined cycle gas turbine (CCGT); coal and gas-fired carbon capture and storage (CCS); nuclear; offshore wind; onshore wind; solar photovoltaics (PV).
- **Chapter 5** draws out key themes from Chapter 2, 3 and 4 in order to provide high level analysis and conclusions, including the implications of cost estimation and future forecasting as they relate to energy policy making.

[3] Available at www.ukerc.ac.uk/support/tiki-index.php?page_ref_id=2863

2. The use and role of electricity cost estimates

2

2.1 Introduction

This chapter examines the importance and differing roles of cost estimates and forecasts in energy policy and the electricity generation industry. Firstly, it examines the key role that cost estimates have had in both shaping policy goals and informing the design of policy to meet those goals, and also the degree of interdependency between these two processes. It then discusses the types of cost estimates that have featured most prominently in policy analyses to date and the possible limitations of such estimates for future analyses. The chapter goes on to present recent cost estimates/projections and examine the uncertainties surrounding cost estimates and the future trajectory of costs.

2.2 Cost estimates in policymaking – and impact of policy on costs

Estimates of electricity generation and/or capital costs – historic, contemporary, and future – are prevalent in analyses undertaken by academics, commercial consultancies and policymakers, all of which feed into energy policy. They are key inputs to cost-optimising energy system models such as MARKAL/TIMES[4], used extensively to create scenarios of future energy systems (HM Government 2009, UKERC 2009, CCC 2010). Cost estimates have informed successive Energy White Papers and Reviews (DTI 2006, DTI 2007, DECC 2011), the supporting analysis for the Renewables Obligation (RO) (DTI 2002b, DTI/Ernst&Young 2007), the 2008 Climate Change Act (HM Government 2008) and for the ongoing Electricity Market Reform process (DECC 2013b, DECC 2013c). They also feature prominently in range of assessments of low carbon and renewable energy such as the 2002 Energy Review (PIU 2002a), the Stern Review (Stern 2006), and the CCC Renewable Energy Review (CCC 2011a). Cost data are also at the core of international publications such as the IEA's World Energy Outlook and Energy Technology Perspectives series of reports (IEA 2012a, IEA 2012b).

Future costs forecasts are heavily influenced by contemporary and historic costs data. Indeed, so called 'experience curves' (or learning curves), which we discuss in more depth in Chapter 3, are an extrapolation of historical trends. Inevitably therefore, views of the likely future of energy costs are to a very considerable degree shaped by data from the past and present. For example, estimates of future costs (the DTI's 'resource cost curves') played a central role in the design of the in defining both the level of the 2002 Renewables Obligation (RO) and the RO buy-out level (Gross *et al.* 2007). More recently, the Committee on Climate Change's assessment of optimal decarbonisation strategies, which form part of its advice on the UK Carbon Budgets, is based on considerations of technology costs (along with carbon price, demand growth, and capital stock turnover), and the 2011 assessment used cost forecasts to construct scenarios out to 2020 and 2030 (CCC 2011b).

Changes in UK government policy towards nuclear power also provide a salient example. The view set out in the 2002 Energy Review (PIU 2002a) was that the focus for energy policy should be energy efficiency and a substantial increase in electricity generation from renewables, with the option for new nuclear power 'kept open' but with 'no current case for further government support' – a view based in part on an assessment of the cost of new nuclear relative to other power generation technologies, together with an assessment of the potential for newer technologies to come down in cost through innovation and learning (PIU 2002a). However, analysis undertaken as part of the 2006 Energy Review compared the levelised cost of nuclear power and other electricity generation options and concluded that the economics of the technology had improved, to the extent that it was economic without subsidy, and that 'new nuclear power stations would make a significant contribution to meeting our energy policy goals' (DTI 2006). This was followed by a White Paper on Nuclear Power (BERR 2008) which confirmed the UK Government's view that, 'nuclear power has a key role to play as part of the UK's energy mix'.

There is therefore a direct and important link between cost data/analysis and government interventions with estimates of costs helping to set the direction and shape of policy. However, policy also helps shape costs. The World Energy Outlook, for example, emphasises the 'criticality of government policy action in influencing the energy landscape going forward'. It further suggests that the future of renewables, their costs and deployment, will be heavily reliant on strong government support (IEA 2010b). The Stern Review makes a similar point, arguing that 'the ambition of policy has an impact on estimates of cost' (Stern 2006). Closely aligned to this is the importance of judgements and assessments that suggest costs will fall as a consequence of increasing deployment. If, as we explore in Chapter 3, technologies are subject to increasing returns to adoption, for example learning effects and economies of scale, then policies to expand deployment can help to reduce costs.

Sections 2.3 and 2.4 outline the principal categories of cost used in policy analyses, review the range of recent assessments of cost for UK power generation technologies, and discuss the treatment of uncertainty with respect to cost estimation.

[4] MARKAL (MARKet ALlocation) is a least-cost optimisation model of energy use, which represents the entire energy system, from primary resources to demands for energy services, see (UKERC 2009) for a more detailed description. TIMES (The Integrated MARKAL-EFOM System) is the most recent evolution of MARKAL.

2.3 Key measures of costs used in policy

General categories of cost

Economists distinguish between variable costs (VC, those costs that vary with respect to output) and fixed costs (FC, those costs that do not vary with respect to output), with total costs (TC) being the sum of fixed and variable costs. A further distinction is drawn between short-run marginal costs (SRMC, defined as the additional cost of generating a unit of electricity, over a time period in which some costs are fixed) and long-run marginal costs (LRMC, the additional cost of generating a unit of electricity, over a time period in which no costs are fixed). The corresponding definitions for average costs are short-run average costs (SRAC, total costs divided by units of electricity generated, over a time period in which some costs are fixed) and long-run average costs (LRAC, total costs divided by units of electricity generated, over a time period in which no costs are fixed). Strictly speaking, marginal cost is the derivative of total cost with respect to quantity but since fixed costs do not change with respect to quantity, then marginal cost can be defined as the derivative of variable cost with respect to quantity. It must also be recognised that in practice, power plant output will be varied in discrete units (such as MWh), not the infinitesimally small change implied by the derivative function (Stoft 2002, Rothwell and Gomez 2003, Weyman-Jones 2009). A useful alternative description of the concept of marginal cost is provided in Weyman-Jones (1986) in which it is described as 'part of the information discovered by trying to find the least expensive way of meeting some future change in output' (pg. 71-72).

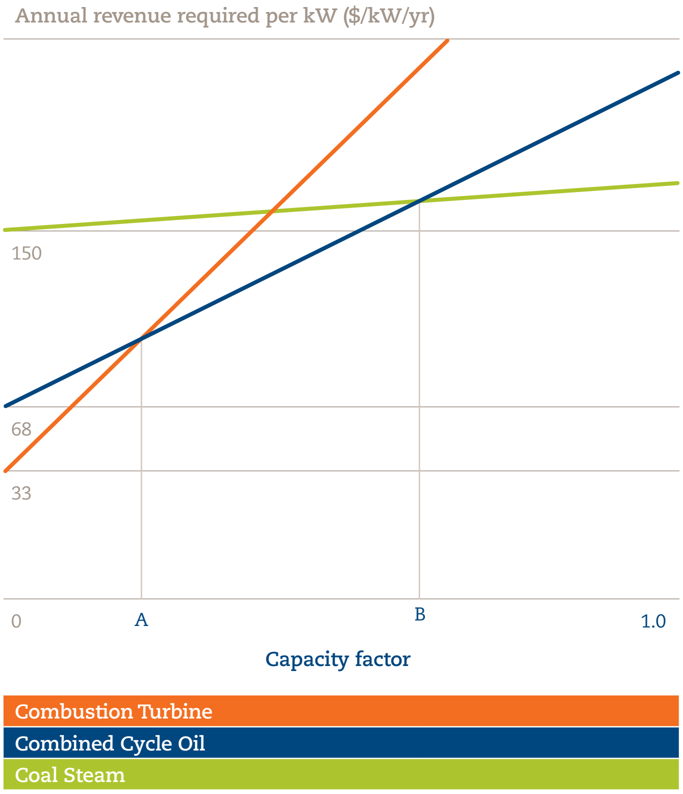
As well as these economists' definition of costs, there are other ways of categorising costs, based on the physical 'thing' that they represent. These include capital costs (the cost of building a power station), operational and maintenance costs (the costs incurred in running and servicing a power station, such as fuel and maintenance costs), transmission and distribution costs (the cost of delivering units of electricity to consumers), retailing costs (for example the cost of providing metering and billing), and decommissioning costs (the cost of dismantling a power station at the end of its life). There is also a particular variant of capital costs, known as 'overnight costs' which can be defined either as the capital costs of a notional power plant if it is assumed that no interest charges are incurred during construction (i.e. 'overnight'), or alternatively as the present-value cost of a plant that would have to be paid as a single sum before the project begins, to pay completely for a plant's construction (Stoft 2002). As we discuss in more detail in Chapter 3 there can be variation between studies as to the extent to which the full range of cost factors are included within the scope of the system/technology in question.

A further differentiation should be made between accounting balance sheets and economic interpretations of costs. For example, a sunk cost (one that cannot be recovered) is still a cost to an accountant and will appear on a balance sheet until it is written off, but is of less importance to an economist because a sunk cost should not (in theory) bear upon subsequent decisions (Rothwell and Gomez 2003).

Each of these categories of cost have specific uses and applications, for example the short-run marginal cost which a power station owner faces will determine the electricity price at which they are prepared to run the plant and sell the output over a short term time horizon, but the long-run average cost (relative to long run electricity prices) is a more important influence on the decision to build a new power station, and also on whether the owner of an existing power station continues to operate their plant over the long term – or chooses to exit the market, sell the plant and do something else with their capital.

Economists and utility planners have in the past used approaches such as 'screening curves' as a tool for preliminary comparison between electricity generation technology options. These curves plot annualised total cost per unit of capacity installed (e.g. kW or MW) as a function of plant load factor, and help 'establish the envelope within which a supply option will be economic', and so 'serves to screen out options that cannot possibly be economic'(Koomey *et al.* 1989). Figure 2.1 on page 15 shows an example screening curve for three technologies, demonstrating how the annual revenue required varies depending on the plant load factors ('Capacity Factor' on the diagram) – and crucially, that it varies differently between technologies. This is because the slope of the screening curve for a particular technology represents the variable costs of operating the plant, and the y-axis intercept represents the annualised fixed costs of the plant (Stoft 2002).

Figure 2.1: Example screening curves for electricity generation technologies



Source: (Koomey *et al.* 1989)

It is important not to confuse the average cost of using a unit of generation capacity, as shown on typical screening curves, with the average cost of a unit of electrical output. The latter is typically described as the (plant) lifetime levelised cost of energy, to which we now turn.

Levelised costs of energy (LCOE)

Although engineers, economists and accountants use a range of cost measures and categories, policymakers have historically focussed in particular on the levelised cost (LCOE), and to a lesser extent, capital cost (capex) because these were (and remain) particularly important cost measures from a societal perspective.

The LCOE calculation incorporates all the costs incurred during the life of a power station, including for example capex, O&M (operations and maintenance), fuel and decommissioning costs, and divides the discounted sum of those costs by the discounted lifetime output from the power station, resulting in a lifetime average (levelised) cost per unit of electricity from the power station. A widely used formulation of the LCOE calculation is shown below (IEA 2005)[5].

$$\textit{Levelised Cost} = \frac{\sum[(I_t + M_t + F_t)(1 + r)^{-t}]}{\sum[E_t (1 + r)^{-t}]}$$

(where: I_t = Investment costs in year t, M_t = O&M costs in year t, F_t = Fuel costs in year t, E_t = Electricity generation in year t, r = Discount rate)

Estimates of LCOE can provide a range functions, including (Gross *et al.* 2010):

- A high level comparison of generating technologies in terms of the relative performance and prospects of each;
- An assessment of cost effectiveness of the contribution of new technologies to various policy goals and whether there is a rationale for intervention (Cost Benefit Analysis, Welfare Assessments, etc.);
- An approximate view of the level of subsidy needed to promote individual technologies, or technology types;
- An assessment of the potential value of investments intended to promote innovation, for example creating markets to allow learning by doing, again using cost projections or technology 'learning curves' that link costs to market growth;
- Input to some economic models of the electricity system, as used for energy scenarios that can inform policy (see section 2.2 above).

Although widely used and cited, LCOE estimates have important limitations/drawbacks. One concern is that different studies may include/exclude key factors such as decommissioning costs, interest during construction, or insurance, and there can be disagreement about whether cost of capital should be common to all technologies or differentiated to reflect different levels of technological maturity and risk. Certainly all these factors, along with judgements about performance and capital cost will differ between studies.

The principal factors not captured in LCOE assessments can be broadly categorised as commercial factors, system factors and economic externalities. Some of these limitations are shared with other measures of cost, but we focus on LCOE limitations here because of its prevalence in the energy policy debate.

The commercial factors not captured by the calculation are as follows: plant lifetime may be longer than 'economic' life; the unpredictability of fuel price (costs) and revenue volatility (electricity volume and prices); the implied cost of the irrevocability of investments; the impact of project size/scale/modularity; the option value that investment in a particular technology may give a utility (Awerbuch *et al.* 1996); the costs of

[5] An alternative approach is the 'annuity' method which involves calculating the present value of the cost stream (giving a lump sum value), which is then converted to an Equivalent Annual Cost (EAC) using a standard annuity formula. Dividing the EAC by the average annual electrical output results in a levelised cost. Provided the discount rate used in calculating the present value of the total costs and the 'levelisation' rate used in the annuity formula are the same then the results will be the same as the IEA method (Gross *et al.* 2007).

information gathering (i.e. the information required to inform an investment decision); future changes to: tax regimes, environmental legislation, government support mechanisms; corporate level taxes – both the absolute level and the details of the tax regime e.g. some tax rules allow the accelerated depreciation of assets – which may affect choices between capital intensive and less capital intensive technologies (IEA 1989); portfolio value, whereby investment in generating technologies whose costs do not co-vary with other technologies can reduce overall costs at any given level of risk (Awerbuch 2000). These limitations help to explain why levelised cost estimates do not necessarily give a good indication of what type of plants will actually be built – see Box 2.1.

The system factors not captured include: transmission costs and other network costs such as impact on system balancing and system security requirements; the impact on state/system level energy security; the degree of flexibility/controllability of power station output and suitability for different operating modes e.g. baseload or balancing services, and relative impact of demand variation.

The economic externalities which may not be reflected include: the value of government funded research programmes; any residual insurance responsibilities that fall to government; any un-priced externalities e.g. CO_2 costs in the absence of a CO_2 tax or CO_2 cap/permits; external benefits such as the value of learning to future generations; and inter-temporal and inter-generational cost issues.

Capital cost estimates (capex)

The discourse around energy policy frequently focuses upon capital costs (or capital expenditure, capex) – the costs of building (but not operating and running) new power stations. Obviously capex cannot capture the entirety of costs which will be incurred in building and operating a power plant during its economic life. The share of capex in total lifetime costs varies considerably between technologies; nuclear power and most renewable technologies having high capital costs and very low running costs and others such as gas-fired power stations having relatively low capital costs but high running (principally fuel) costs.

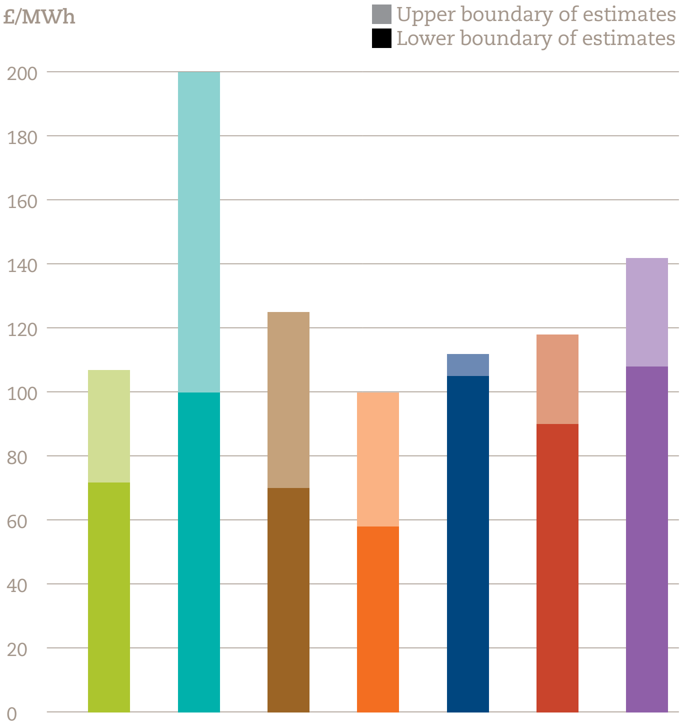
Capex on its own is of course an incomplete representation of the total cost of producing electricity, which is the reason that levelised costs are used more widely. Apart from neglecting fuel and other operation costs, which may dominate marginal and total costs, capex has no time dimension. Economists argue that this means that capex 'provides useful information but only for the purpose of finding fixed costs' and that 'they cannot be compared with other costs until levelised' (Stoft 2002). Nevertheless, capex estimates play a very important role in policy analyses. This is particularly the case for nuclear and many renewable generation technologies where the capital cost can be the overriding determinant of cost out-turns (Greenacre *et al*. 2010, Harris *et al*. 2012). Policymakers are also often concerned about the overall volume of investment required to deliver policy objectives, for example the UK Government estimate that approximately £75 billion of investment is required in electricity generation capacity by 2020 to meet its energy policy goals (DECC 2012b).

2.4 The range of LCOE estimates – past, present and future

2.4.1 Recent cost estimates and recognition of uncertainties

Figure 2.2 summarises the ranges of LCOE estimates reported in analyses commissioned by DECC and the CCC during the last two years, for projects with construction starting around the time the analyses were published (i.e. these are estimates of current costs, not forecasts for projects starting some years into the future).

Figure 2.2: Range of recent cost estimates for large-scale electricity generation in the UK



Technology	
Nuclear	CCGT + CCS
Offshore wind	Coal
Onshore wind	Coal + CCS
CCGT	

Source: (Mott MacDonald 2010, Arup 2011, Mott MacDonald 2011, Parsons Brinckerhoff 2011, DECC 2012a, DECC 2013b, Poyry 2013).

Box 2.1 What to build and what to run? – investment decisions and the unit commitment problem

Investment in new power stations under liberalised markets is subject to a complex range of factors, few of which are captured in a simple comparison of levelised, capital or indeed many other categories of costs. Decisions on when and what to invest in will be based on their view of how their own actions will be responded to by their competitors, on their perception of the value of a particular investment as part of their generation portfolio, or the option value of waiting for more information (Bazilian and Roques 2008). As the authors explain in detail in a previous UKERC report (Gross *et al.* 2010, Gross *et al.* 2007) under many circumstances investors are likely to prefer to invest in power generation technologies such as combined cycle gas turbines (CCGT) even if other technologies such as renewables and nuclear power appear to have similar levelised costs. This is because CCGT plants are typically 'price-makers' which are able to pass fuel prices onto customers (and so largely removing fuel price and revenue risks) whereas high fixed costs nuclear and renewable plants are 'price-takers' which remain more exposed to revenue risk (Gross *et al.* 2010). The consequence is that policy which aims to deliver investment in high fixed cost technologies must do more than simply equalising levelised costs (net of support) across technologies.

Furthermore, none of the cost categories described in this section will on their own identify what plants should actually be operated to satisfy system demand for a particular period. The answer to that question requires a solution to the 'unit commitment problem' i.e. given a particular mix of available generating plant (i.e. units), what is the actual mix that should be operated (i.e. committed) that will satisfy demand for a defined demand period at minimum cost? Note the word 'unit' here relates to a power station generating set, not units of electrical energy such as MWh. Solving the unit commitment problem is an optimisation process using data from all available generating plants on e.g. fuel cost curves, maintenance cost curves, unit start-up costs, unit ramping rate limits, unit capacity limits, and unit minimum up and down times (Sheble and Fahd 1994).

These issues are further complicated because in liberalised markets such as the UK with no (or very limited) central despatch of generation it is not the system operator's job to decide which plants will actually run. Instead, policymakers and regulators must try to design and structure a market which delivers investment in, and efficient dispatch of, a mix of actual generation capacity which approaches the theoretical least-cost solution to the unit commitment problem (Stoft 2002).

LCOE estimates also feature strongly in the ongoing discussions around the level of support to be offered to low carbon generators (via the strike price set by the Contracts for Difference) under the Electricity Market Reform process (DECC 2011, DECC 2013a), and in technology specific cost reduction aspirations, such as the drive to reduce the cost of offshore wind (Offshore Wind Cost Reduction Task Force 2012, The Crown Estate 2012).

A number of recent analyses explicitly recognise the degree of uncertainty in their estimates (Mott MacDonald 2011, Parsons Brinckerhoff 2011, Parsons Brinckerhoff 2013). Indeed Parsons Brinkerhoff particularly emphasise the high degree of uncertainty in cost estimation and analysis, potential cost reductions from learning and the significant impact that the cost of capital (i.e. interest on debt and dividend payments for equity holders) has on the relative costs of different generating technologies. If a lower cost of capital is assumed this favours technologies that are relatively capital intensive and have long lifetimes, i.e. all low carbon technologies are favoured over unabated fossil fuel plant, while nuclear and most renewables are favoured over CCS and bioenergy. If, on the other hand, a higher cost of capital prevails then low carbon is penalised in favour of unabated fossil fuels.

In their 2011 report for DECC, Parsons Brinckerhoff are clear that 'In using the estimates prepared by PB the inevitable uncertainties need to be recognised. Costs should be considered in the light of the AACE International Recommended Practice 18R-97'. A summary of that recommended practice is included in their 2011 and 2013 reports, and an adapted version of the AACE cost estimate classifications matrix is shown in Table 2.1 below. It is implied in the Parsons Brinckerhoff report that their cost estimate ranges are in the 'Class 5'category (i.e. those with the largest degree of uncertainty) with an expected accuracy range between minus 50% and plus 100% (with a potentially smaller range for more mature technologies). This degree of uncertainty results in part from the generic (rather than site-specific) nature of the estimates, and also that the AACE classifications are more usually applied to specific projects.

Figure 2.3 compares cost estimates for leading electricity supply options made in studies commissioned by the UK Government in 2011 (Arup 2011, Parsons Brinckerhoff 2011) with those made as part of the analysis underpinning the 2006 UK Energy White paper (DTI 2006). The comparison reinforces the point that cost estimates can vary considerably even over relatively short periods. For example, over the five years separating these two sets of estimates, estimated costs for CCGT had risen by nearly 80%, nuclear by around 75%, and onshore wind by over 40% (on an inflation adjusted basis, using the midpoint of the central ranges). There are a wide range of factors which have influenced these cost increases, including for example, gas and carbon prices in the case of CCGT, design changes in the case of nuclear, and also the fact that some of these technologies are at an early stage of development when there is inevitably a greater degree of uncertainty over costs and technology performance. These factors are discussed in the technology case studies in Chapter 4.

Figure 2.3: Comparison of 2006 and 2011 cost estimates[6]

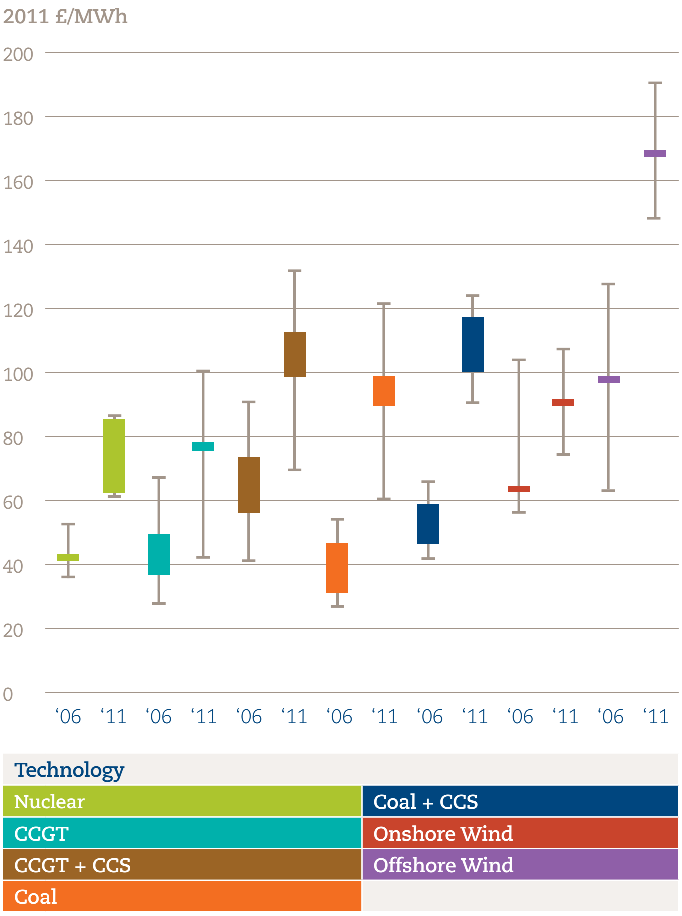


Table 2.1: AACE cost estimate classifications, adapted from AACE International (2005)

Estimate Class	Typical Use	Typical Estimating Method	Typical Expected Accuracy Range
Class 5	Concept Screening	Capacity Factored, Parametric Models, Judgement, or Analogy	Low: -20% to -50% High: +30% to +100%
Class 4	Study or Feasibility	Equipment Factored or Parametric Models	Low: -15% to -30% High: +20% to +50%
Class 3	Budget Authorisation, or Control	Semi-Detailed Unit Costs with Assembly Level Line Items	Low: -10% to -20% High: +10% to +30%
Class 2	Control or Bid/Tender	Detailed Unit Costs with Forced Detailed Take-Off	Low: -5% to -15% High: +5% to +20%
Class 1	Check Estimate or Bid/ Tender	Detailed Unit Costs with Detailed Take-Off	Low: -3% to -10% High: +3% to +15%

[6]The cost analyses on which this chart is based typically calculate a range of levelised costs based on a central set of assumptions and an extended range based on wider variations in the input parameters. In Figure 2.3, the central assumptions are represented in the coloured blocks and extended range in the black lines extending from each block. The exceptions are the 2011 entries for onshore and offshore wind which reflect the low, medium and high estimate approach adopted in the Arup 2011 analysis.

[7]The historic contemporary estimates are shown in the left-hand data series and the forecasts are shown in the right-hand data series. Trend lines are shown as solid lines for contemporary estimates, and as dotted lines for the forecast data. Note that all values are converted and inflated to 2011 GBP using historic exchange rate data from the Bank of England spot exchange rate against £ sterling and annual average long run inflation data from the UK Office of National Statistics. The forecast data on the right-hand side of the chart shows the full range of the collated estimates, and therefore reflects the different input assumptions, forecasting techniques and sensitivities examined in the literature.

These observations highlight the difficulties facing policy makers where there is both a considerable degree of uncertainty over technology costs at the time that those estimates were made (represented by the wide ranges associated with each estimate), and uncertainty over how those costs will change over time (represented by the differences between the 2006 and 2011 estimates shown above). We return to this theme of uncertainty in Chapter 5.

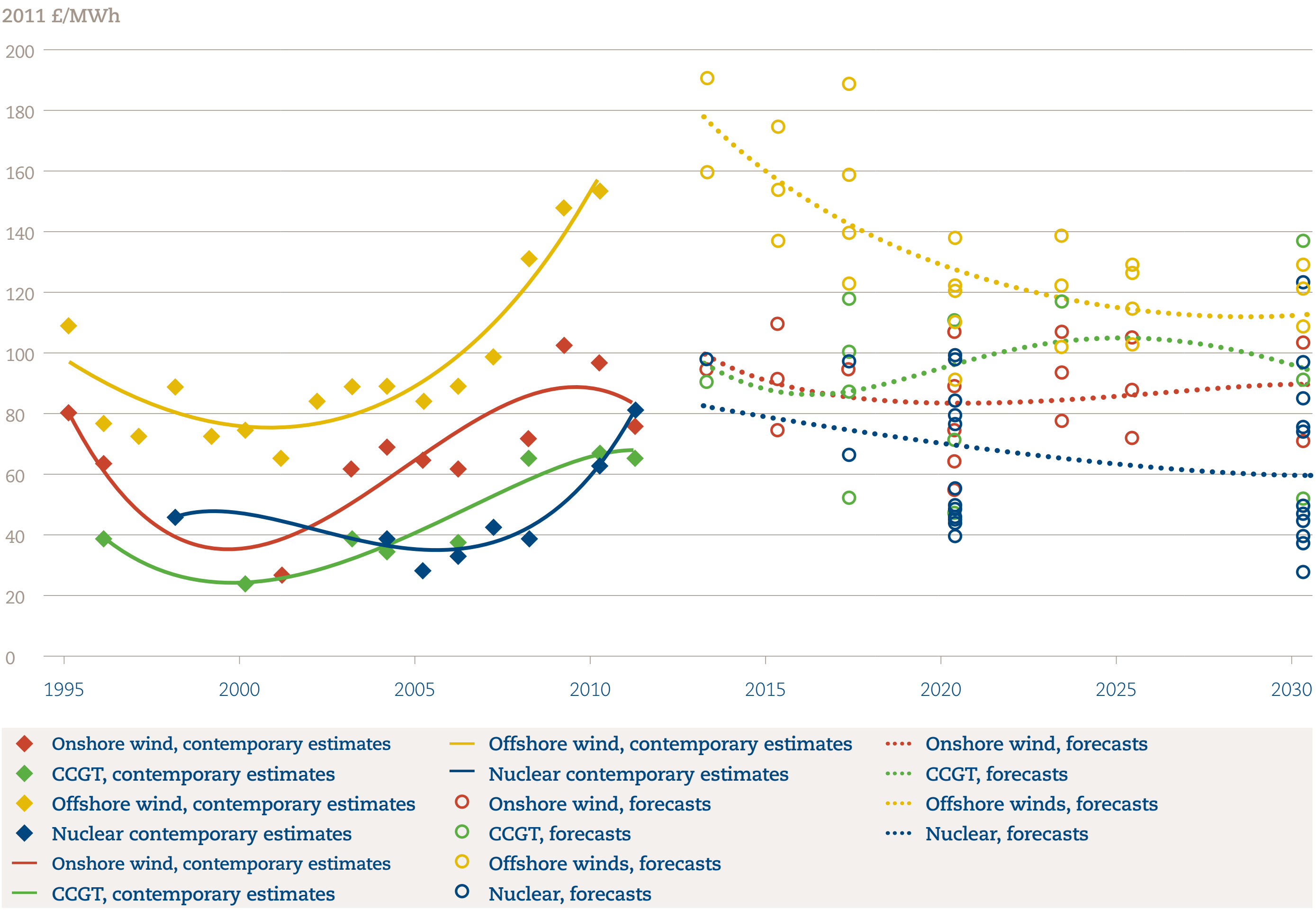
2.4.2 The range of cost estimates past and future

As part of the technology case studies which are described in detail in Chapter 4, the project team collected cost estimate data which are used in Figure 2.4 below to plot the in-year mean of European estimates of contemporary LCOE from 1995 through to 2011, as well as the range of UK-specific LCOE forecasts from 2013 through to 2030 for four major electricity generation technologies. In addition, Figure 2.5 summarises the trajectory of contemporary capex estimates from the year 2000 onwards and presents the in-year mean capex value for each of the six technologies covered by the case studies.

Figure 2.4 shows that there is considerable variation in LCOE estimates over time for all the analysed technologies, and contrasts the direction of past variation over time with future forecasts. The clear trend for historic estimates for all of the technologies shown is one of rising costs from the early to mid-2000s onwards, with offshore wind and nuclear power apparently on significantly steeper upward trajectories than onshore wind and CCGT. Turning to forecasts, estimates for offshore wind in particular suggest a relatively steep reduction in costs over the next 10-15 years, followed by a levelling off, albeit still at a point higher than the lowest of the historic estimates. Forecasts for onshore wind and nuclear suggest that relatively smaller cost reductions are anticipated for these technologies. Forecasts for CCGT costs do not follow the same trajectory, although this may in part be linked to assumptions over future fuel prices and CO_2 emissions costs rather than the underlying technology cost. We return to these issues in more detail in Chapters 4 and 5.

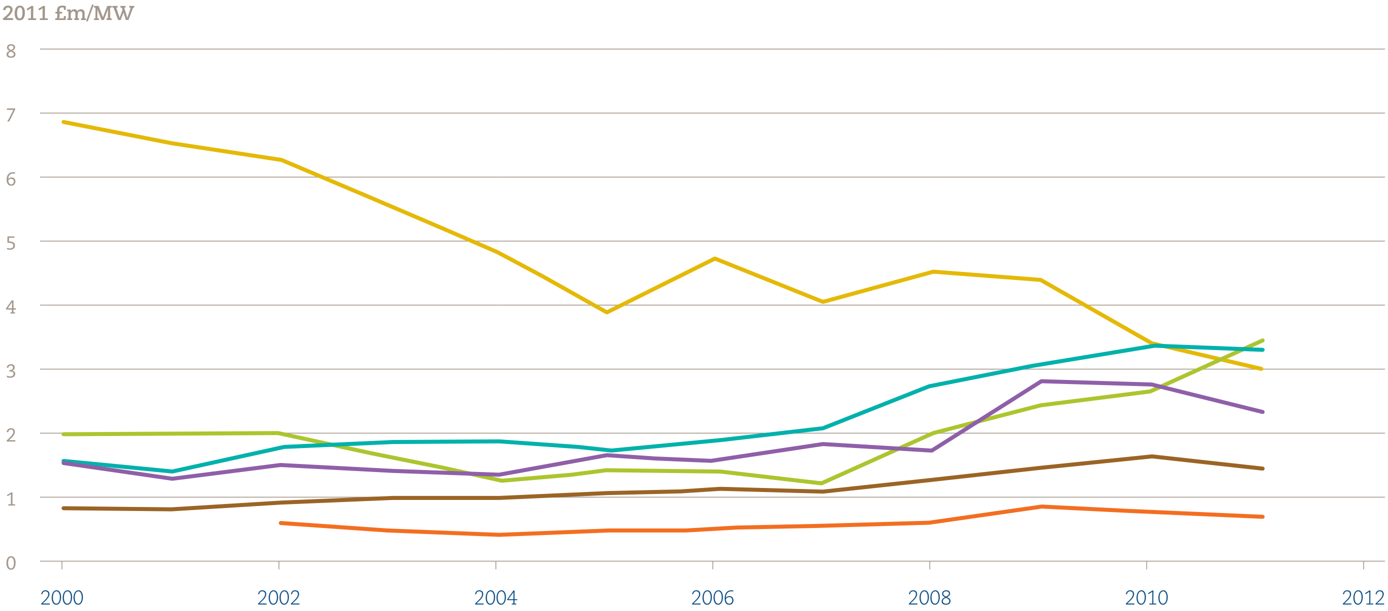
In general, forecasts tend to show a much smoother and more consistent, often downward trajectory, although there is still a considerable range of estimates within specific future years. Of course, estimates made in the past would inevitably be expected to change from one year to the next as technology costs responded to real techno-economic conditions, and we discuss the reasons why estimates of costs out into the future are often expected to fall in Chapter 3.

Figure 2.4: Range of LCOE estimates, in-year mean and UK-specific forecasts



Source: (UKERC analysis)[7]

Figure 2.5: Trajectory of in-year mean capex values



Technology		
Nuclear	Onshore wind	CCS
Offshore wind	CCGT	PV

Source: (UKERC analysis)

2.5 Conclusions on costs, policy and cost estimates

Electricity cost estimates are a critical input to policy analysis and have a strong influence over both the overall direction and goals of policy, and the design of policy to achieve those goals. Cost estimates and projections have played a central role in the policy formulation process, aiding in the identification of viable options and the assessment of the economic impact of a range of generation mixes.

The prospects for cost reductions in low carbon technologies have played a key role in analyses of the affordability of achieving CO_2 emissions reduction targets. More specifically, technology learning rates and the resultant cost reductions inform the conclusions that CO_2 emissions can be abated at relatively low cost and that policy is required to drive deployment so that those cost reductions can be realised.

This chapter has highlighted a degree of circularity in the relationship between cost estimates and policy, in that perceptions of current and future costs for electricity generation technologies can influence decisions over which technologies are considered appropriate for policy support (of whatever nature), and that such policy support can then drive deployment of those technologies, which in turn can help to reduce costs. To a degree at least it appears that projection of cost reduction potential may be a self-fulfilling prophesy.

The limitations of the cost metrics commonly used in policy analyses such as the LCOE measure are in principle understood, and can be broadly categorised as limitations in extent (such as the inability to capture all economic externalities), limitations in method (such as determination of the appropriate discount rate or the assumed plant load factor), and limitations in applicability (such as the degree to which they are able to indicate how market participants will act). However, key issues remain over how these limitations can be addressed, and in determining the appropriate policy response.

It is also clear that considerable uncertainties remain, both over the accuracy of contemporary cost estimates and the future trajectory of costs. The theory that underpins much of the cost estimating and forecasting literature and analysis is considered in the following chapter. The enduring challenge for policymakers is how to develop approaches and mechanisms that are robust in the face of these uncertainties, and explicitly recognise that uncertainty over costs estimates seems likely to remain. Finally, policy must also recognise that the categories of costs which matter from a societal perspective and in the setting and achieving of broad policy goals are not the only costs that influence how market participants will actually behave – and in the UK's liberalised electricity market it is important that policy addresses this challenge.

3. Falling costs? Theory, Drivers and Forecasting

3

3.1 Introduction

This chapter considers the reasons the costs of products or processes are expected to go down over time and then goes on to examine experience curves and engineering assessment, the principal methodologies used to make forecasts and projections of future costs in power generation. The chapter is based upon a systematic review of the literature covering both the evolution of the subject and the latest thinking.

The discourse on cost reduction and learning effects has its roots in the theory and literature on increasing returns to adoption, theories of learning and models charting the relationship between market growth and costs (so called learning or experience curves) (Arrow 1962, Arthur 1994). From this arose a sub-set of studies focusing on cost reduction specifically in the energy arena. This literature is principally concerned with the costs of technologies and systems rather than related issues such as the cost of capital (cost of borrowing, perceptions of risk etc). However, as we discuss below, the relationship between costs, prices and a range of market and policy factors is complex. It is clear from the evidence reviewed that this is a discourse that has not yet been resolved, continues to evolve, and leaves much still to understand about the interaction of costs drivers, trajectories and forecasting.

3.2 Sources of cost reduction

The tendency for technologies to show increasing returns to adoption is a well-established tenet of the economics of innovation. The more a technology is taken up by users, the more it will be produced in greater volumes by more manufacturers, and thus the more likely that costs will go down and efficiencies will go up, leading to even further adoption, production, and deployment resulting in a 'virtuous spiral' of continued cost reductions. Arthur (1994) identified four major classes of increasing returns to adoption: *network externalities, adaptive expectations, economies of scale and learning effects.*

Network externalities describe the effect that the use of a good or service by one person or entity has on the value of that product to others. Also described as co-ordination effects (Pierson 2000), these occur where technologies are linked and need to be compatible, or a system is required. When a network externality occurs, the value of a product or service increases as more people use it. The telephone is a classic example whereby the more people that own one, the more useful and valuable the technology becomes to each of them. Other examples include computer hardware and software, video tape or DVD formats, road vehicles and refuelling systems.

Adaptive expectations refers to the phenomenon whereby as a leading design emerges consumer uncertainty is reduced and more consumers are encouraged to adopt the leading design, further encouraging its adoption and hence feeding back into yet more widespread use. Adaptive expectations also apply to investors and in commercial enterprises.

Economies of scale can arise in the manufacturing of generation technologies from the reduction in average unit costs as fixed costs are spread over increasing production volumes, with the potential result being a virtuous spiral of further increases in demand and cost savings. They can also arise at a project/plant level. Cost savings can be delivered per MW installed and per MWh through increasing the total installed size of a power station and/or the major components. Examples of the latter include the scaling up of UK coal-fired steam turbines during the 1960s and 1970s, albeit not without significant challenges (Hannah 1982), and wind turbines increasing in size from around 200kW or less in the 1980s to the multi-MW scale (Arantegui *et al.* 2012). Both instances yielded considerable economies of scale.

Learning effects reflect product or system improvements and cost reductions as experience is gained in the development, production, deployment, and application of a technology. The main categories of learning effects typically cited in the literature are ***learning-by-researching, learning-by-doing, learning-by-using,*** and ***learning-by-interacting*** *(Schaeffer et al. 2004).*

Learning-by-researching (or *by-searching*) is essentially self-explanatory. R&D activity tends to focus on what Schaeffer terms 'know-why' knowledge i.e. fundamental concepts and principles. For Junginger et. al (2008), it represents improvements related to the innovation process and the absorptive capacity of the firm, and is dominant not only in the invention stage but also during the diffusion and saturation stages.

The concept of *learning-by-doing* – the 'know-how' of knowledge – was first articulated by Theodore Wright in the 1930s who observed that the labour cost of producing an aircraft frame declined with the number of frames produced. This idea was formalised in a paper by Kenneth Arrow in 1962 which proposed that learning was the product of experience and of problem solving (Arrow 1962). In effect, at the level of the firm there are actually two outputs, one of which is the product or service itself and the other is gradually accumulating experience (Isoard and Soria 2001). This so-called learning effect may be measured in terms of a reduction in the unit cost (or price) of a product as a function of experience gained from an increase in its cumulative capacity or output (Jamasb and Kohler 2007).

Learning-by-using refers to the gains in knowledge from use of the product by consumers. The user's experience and feedback help to understand the performance and limitations of the product and to learn more about the users' needs. It also allows firms to carry out modifications or to suggest them to the manufacturer (Junginger *et al.* 2008).

Learning-by-interacting refers to the interactions between actors like research laboratories, industry, end-users and policy makers that can enhance the diffusion of knowledge (Junginger *et al.* 2008). In essence, learning-by-interacting is about knowledge exchange regarding product or system problems and solutions. This should give rise to product or process innovations with consequent increases in efficiency and reductions in cost (Foxon 2003).

With numerous sources of scale economy, learning and innovation, the expectation of costs falling through time, particularly for new and emerging technologies, is certainly a reasonable starting proposition. How then to assess and quantify the potential for costs to fall? Two principal categories of methodologies are widely used to attempt to quantify this reduction and estimate future costs:

- Forecasting by means of technical *engineering assessment*, and
- Extrapolation from historical data by means of *experience curves* (often taken to be synonymous with learning curves, though, as explained below, some commentators now distinguish between the two terms).

Some commentators also use of quantitative tools such as *parametric modelling* (or parametric costing) (Mukora *et al.* 2009) and assess learning investments and needs using logistic curves (Pan and Köhler 2007). In the following sub-sections we explore the principal methodologies themselves and their advantages, limitations, and refinements.

3.3 Forecasting cost reduction – 1. Engineering Assessment

Engineering assessment disaggregates a technology system into its component parts and draws on engineering and scientific expertise for a detailed analysis of potential technical change and possible cost and efficiency improvements (Mukora *et al.* 2009). Typically, assessment of technologies places them on a spectrum that ranges from 'emerging' to 'mature' (Chapman and Gross 2001) with emerging ones considered to have the greatest potential for further development and cost reduction through innovation and returns to scale.

Our review of the literature revealed relatively little evidence that analyses the methodological issues associated with using engineering assessment for assessing electricity generation costs. However in most instances a technology system is disaggregated into subsystems and components to analyse specific contributions to, for example, total mass or cost (an overview is offered by Mukora *et al.* (2009)). The individual effects are then recombined for the whole system using weighting factors depending on the contribution of the effect. Part of the assessment may be to identify the main drivers of cost (e.g. labour, steel, other industrial commodities etc.) in order to build a composite cost index (Arup 2011).

Engineering assessment is thus a two-stage process of first, assessing the current technical and engineering features and costs of a technology and then second, assessing the prospects for development of those features and their impact on future cost and efficiency. Analysis of future cost or performance often combines a degree of qualitative review, often based upon expert judgement, with quantitative evaluation based on experience in estimation and parametric modelling (see below). In some instances, an assessment may be done by categorising the technology and forecasting its technological progress by benchmarking similar or related technologies whose progress is known (Mukora *et al.* 2009). Nevertheless, even with these techniques, satisfactorily representing and forecasting technical change, especially for early-stage technologies, remains a significant challenge (Mukora *et al.* 2009).

3.3.1 Strengths, limitations and refinements of engineering assessment

Engineering assessment has the potential to provide a detailed and accurate analysis over a range of time periods. Such assessment can provide an understanding of the engineering and technical factors that drive cost reduction, help identify the scope for technical progress, and provide insights into how any limitations of current designs can be overcome (Mukora *et al.* 2009).

A key advantage of engineering assessment is that it need not rely on previous trends in cost reduction – trends that may not be repeatable, or are uncertain because market experience is limited. A related strength is the potentially greater ability of engineering assessment compared to experience curves to provide insight into possible discontinuities (i.e. step changes and transitions) in the trend of technological development trajectories and thus to anticipate and factor in radical, as opposed to incremental, change (Mukora *et al.* 2009).

The main disadvantage is that engineering assessments based on expert opinion can differ, and may be open to interpretation and manipulation or excessive optimism (Chapman and Gross 2001, Schaeffer *et al.* 2004). Assessments are also open to straightforward error, both in terms of how to parameterise the costs of a product or process and in terms of the data input for each parameter (Koonce *et al.* 2007).

For new technologies in particular, cost estimates may vary widely. Estimating costs in the early stages of technology development is inevitably difficult. For example, designs for a cost-reducing technology of the future may still be in conceptual form, providing little concrete data. Thus, factors affecting cost are likely to be uncertain, and proper evaluation may only be possible when a production design is finalised (Mukora *et al.* 2009).

Parametric modelling

The engineering approach can be refined through the use of parametric cost modelling, a technique which is applicable to products or technologies in all stages of development, and which uses 'cost estimation relationships' to define links between a specified set of characteristics and cost (Mukora *et al.* 2009). This allows for the identification of relationships that reflect the functional, mathematical link between the characteristics of an item and its cost, which are in turn derived from past experience and from engineering expertise. With this approach, total cost is assessed based upon these defined physical and performance characteristics and their relationships to the costs of specific components.

The strength of parametric modelling lies in its capacity for estimating and exploring the impact of broad design changes. However, its weaknesses, according to Mukora *et al.* (2009), are that it has limited relevance for longer-term forecasting, that its emphasis is on incremental not radical change, and that results are dependent on accurately specifying the cost estimation relationships.

3.3.2 Conclusions on engineering assessment

Engineering assessment for cost forecasting purposes has several limitations and uncertainties. However, the approach does play an important role by disaggregating and analysing the technical and engineering factors underlying potential future cost reduction in energy technologies. Cost factors may be parametrically modelled, allowing sensitivity to key drivers or changes to be explored. Engineering assessment offers advantages in the early stages of technology deployment, where the lack of historical cost and deployment data militates against the use of experience curves (Greenacre *et al.* 2010). It also permits disaggregated assessment of sensitivity to change in key cost parameters.

3.4 Forecasting cost reduction – 2. Experience Curves

In its traditional form an experience curve expresses the relationship between the cost of a product or process and its cumulative production or deployment. The terms 'experience curve' and 'learning curve' are often taken to be interchangeable. However, a distinction is made by some commentators between learning curves which refer only to short run costs such as labour and materials, and experience curves which refer to all costs over the longer term and include the combined effects of learning, specialisation, investment and scale. This report follows the broader, longer term definition and thus for consistency uses the term 'experience curve' over 'learning curve'.

This relationship between cost and deployment may be historically descriptive (i.e. the experience curve describes what has already happened to actual costs and deployment in the past); alternatively, the curve may represent a projection into the future (where the curve relies upon assumed learning and deployment rates going forward). In the case of future projections, the cost trajectory is typically anticipated to be downwards, implying a beneficial causal relationship between capacity increases over time and the cost of production and deployment arising from such factors as learning by doing, advances from research, scale economies, and other returns to increasing adoption. However, as we shall see in later sub-sections, this relationship may be neither as simplistically causal nor as inevitably cost-beneficial as is typically conceived.

As noted, the experience or learning curve approach originated with Wright in the 1930s who observed not only that the labour cost of producing an aircraft frame declined with the number produced but that the rate of reduction remained constant with each doubling of cumulative production (Coulomb and Neuhoff 2006, Weiss *et al.* 2009). This idea was formalised in a paper by Kenneth Arrow in 1962 which proposed the notion that declining labour cost (an expression of the reduction in required manufacturing labour time) is a result of growing experience, and that the productivity of a firm increases as the cumulative output for the industry grows (Arrow 1962). Four years later, the Boston Consulting Group extended this concept of learning to the dynamics of total production costs as a function of cumulative production (including research, capital, administration and marketing, and not simply manufacturing labour costs). This is generally referred to as the experience curve approach (Junginger *et al.* 2008, Weiss *et al.* 2009).

The so-called 'one-factor' experience curve model operationalises the explanatory (independent) variable 'experience' using as a proxy some cumulative measure of production or deployment. Changes in cost typically provide a measure of learning and technological improvement, and represents the dependent variable (Nemet 2006). The key characteristics of the traditional experience curve are that costs are assumed to reduce, rather than remain static or increase, and that, in theory at least, unit cost declines by an approximately constant percentage with each doubling of cumulative production or deployment (Ferioli and Van Der Zwaan 2009). The relationship between cost and deployment is therefore (again in theory) a straight line when shown on a log-log scale (Schaeffer *et al.* 2004).

The central parameter in the experience curve model is the exponent defining the slope of a power function. This parameter is known as the learning coefficient and can be used to calculate the learning rate and its inverse, the progress ratio. Thus, if a cost has reduced from 100 to 80 as production has doubled then the progress ratio equals 80% and the learning rate is 20%. Note that the term 'progress ratio' is used at least as often as 'learning rate' and this can lead to confusion since a higher (i.e. more cost-reducing) learning rate means a lower progress ratio. Conversely, a higher progress ratio means a slower cost reduction rate.

In order to use the experience curve model as a tool for estimating future cost reductions over a specified time period, two assumptions must be made: an assumption regarding the learning rate (or progress ratio) during the forecast period; and an assumption about the rate of future production or deployment of a product or technology. This latter assumption allows the x-axis of an experience curve graph to be converted from one depicting cumulative capacity to one showing time over some chosen future period. The experience curve can now be used to estimate reductions in cost over time and differing cost levels at specific moments in time[8].

As noted, in the simple one-factor curve version of the experience curve, cumulative output as a proxy for experience is the only explanatory variable. In a two-factor curve, factors independent of market size, such as learning-by-researching, provide an additional explanatory variable (Junginger *et al.* 2008). We return to these issues below.

The question of whether economies of scale should be included in the 'experience effect' is open to debate. The relative roles of economies of scale vs. learning effects are discussed in a number of recent papers (Wilson and Grubler 2011, Grubler *et al.* 2012, Wilson 2012) and the interaction between scale, unit size, market growth rates and policy is both vexed and complicated. It is also likely to differ considerably between technologies, as we discuss in Chapter 4. Neij *et al.* (2003) suggests that the connection and overlap between the two is so great that it is difficult to separate them. However, learning by doing and researching are clearly distinct from scale effects and indeed from each other. Moreover, there are possible additional explanatory variables besides these and thus some commentators, such as Yu (2011), advocate the construction of multi-factor curves which attempt to factor in additional cost drivers such as input prices. We return to this below.

Many studies have used the concept of experience curves to assess the cost trajectories of energy generation technologies (Coulomb and Neuhoff 2006). Within the wind sector, for example, studies have focused both on different geographical systems, from global experience curves e.g. Junginger *et al.* (2005) to national ones (Neij *et al.* 2003, Greenacre *et al.* 2010) and also on different system levels, from the levelised cost of electricity (Ibenholt 2002, IEA 2000) to the capital costs of wind farms (Junginger *et al.* 2005, Klaassen *et al.* 2005), to the price of wind turbines (Neij *et al.* 2003).

A primary significance of the experience curve concept is that it implies that expensive new technologies may become cost competitive with incumbent ones once deployment of the technology has provided sufficient learning. There may be some evidence that the 'gap' between incumbent and emerging technologies may not fall if incumbent technologies experience cost reductions of their own (McVeigh *et al.* 1999). Nevertheless, the potential for learning has become one of the key rationales for government support for low carbon technologies and the so-called 'buying down' of costs (Gross *et al.* 2012). Furthermore, experience curves are also a key part of energy sector and macro-economic models that analyse the costs of adapting economies to low carbon futures (Coulomb and Neuhoff 2006). Experience curves are examined in more detail in the following section.

[8] As we discuss later, identification of the temporal starting point for the curve can be problematic for relatively immature technologies which may experience cost increases in the early years of deployment.

Box 3.1 Learning rates in the energy sector

Overall, the literature on learning rates has led sometimes to the use of a general "rule of thumb" rate of 20% for the energy sector with the exception of nuclear power (IEA 2000, McDonald and Schrattenholzer 2001, Jamasb and Kohler 2007). However, as one might expect, energy experience curves reflect a wide range of learning rate values.

Kromer (2010) states a range of between less than 3% and over 35% cost reductions associated with each doubling of output. Kahouli-Brahmi (2008) suggests an even greater range of 1% to 41.5% for learning-by-doing rates and observes that while mature technologies such as coal and oil show relatively low learning rates of 4% on average, renewable energy technologies tend to exhibit higher rates, with solar PV, for example, showing rates of around 20% (Albrecht 2007, Ferioli and Van Der Zwaan 2009).

For many technologies, learning rates appear higher in earlier stages. Thus coal development in the US from 1948 to 1969 showed rapid learning in contrast to later evidence between 1960 and 1980 (Jamasb and Kohler 2007). Gas turbine data also show evidence of learning rate depreciation. Albrecht (2007) reports that for gas turbines the learning rate declined from 20% to much lower rates of around 5 to 10%, and finally towards more or less stabilised prices. The same, says Albrecht, is true for wind generated power. However, this is not a view supported by Jamasb & Kohler (2007) who contend that wind energy has shown a wide range of learning rates with no obvious pattern across either locations or time periods (i.e. early versus late development stages). Solar PV in general has enjoyed faster rates of learning than other renewable technologies (Jamasb and Kohler 2007).

3.4.1 Uses and strengths of experience curves

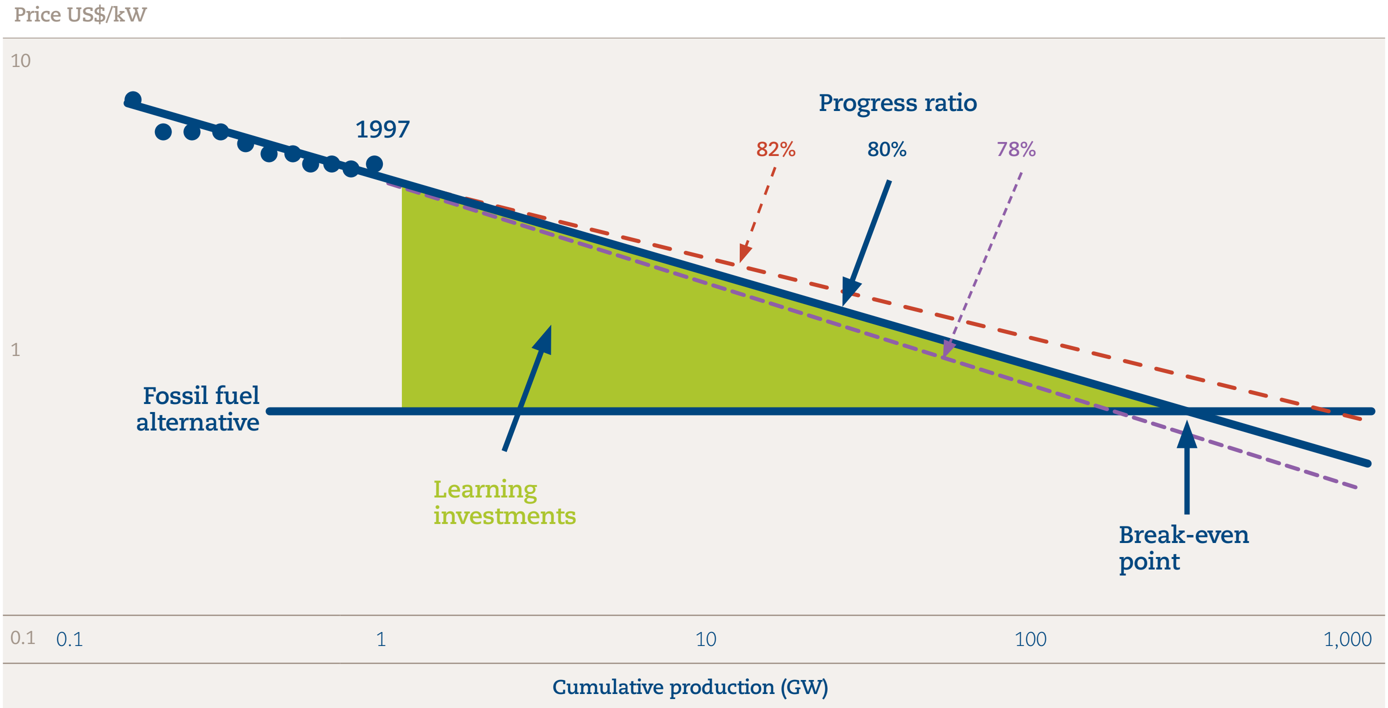
Experience curves are tools for describing, analysing and extrapolating the cost trends of processes and technologies. As such, they have been used extensively for planning at the corporate level and also as a tool for energy policy making at the governmental level (Ferioli and Van Der Zwaan 2009). In theory, as shown by Figure 3.1, they can be used to indicate the likely deployment level and therefore investment needed to make a technology competitive (Junginger *et al.* 2008, Ferioli and Van Der Zwaan 2009); though an experience curve does not forecast when the technology will break-even unless assumptions are made regarding deployment rates (IEA 2000). In addition, they can help in the allocation of scarce resources for innovation (Jamasb 2007), and provide a method for evaluating both the cost effectiveness of public policies to support new technologies and for weighing public technology investment against environmental damage costs (Nemet 2007).

Commentators such as Nemet (2006) and Neij (2008) identify a number of uses and advantages for experience curves in the energy arena. Firstly, they illustrate the approximate rate of historic cost reduction for different types of technologies. Secondly, the introduction of experience curves into energy models makes it easier to integrate technology change into energy-system analysis and scenario planning. This can help indicate the level of investment required to 'buy down' the cost curve, and argues Neij (2008), it shows the benefits to society of early investment in emerging technologies. Thirdly, experience curves illustrate the need for an initial market in order to cut costs. An initial market provides opportunities for learning which should, in turn, lead to cost reductions. Such markets may be developed through early adopters, niche markets, or policy measures that support market expansion (Gross *et al.* 2012).

Experience curves provide an appealing model for several reasons (Nemet 2006). First, studies of the origin of technical improvements provide a narrative that is consistent with the idea that firms learn from past experience. Second, the availability of the two empirical time series required to build an experience curve – cost data and production/ deployment data – facilitates testing of the model. As a result, a large body of empirical evidence has emerged to support the model (although Nemet cautions that data quality and uncertainty tend to be infrequently assessed even though they can have a large impact on results). Third, experience curve studies point to the generally high goodness-of-fit of power functions to empirical data over several years, or even decades, as validation of the model. Fourth, the dynamic aspect of the experience curve model – that the rate of improvement adjusts to changes in the growth of production – makes the model superior to forecasts that treat change purely as a function of time. Finally, the reduction of the complex process of innovation to a single parameter, the learning rate, facilitates its inclusion in energy supply and computable general equilibrium models.

One important validation of the experience curve model is provided by Alberth's (2008) study of energy experience curves, where results indicated that the one-actor curve could be a useful forecasting model when forecasting errors were considered in their log format. It should however be noted that Alberth's case studies were confined to only three technologies – CCGT, Solar PV, and Ethanol – and the last year of data was from 2004, i.e. before the significant cost increases experienced since the middle of the last decade. The fact therefore remains that extrapolating cost reductions over long-time frames and large assumed capacity expansions, whilst potentially providing valuable insight, requires caution (Greenacre *et al.* 2010).

Figure 3.1: Break-even point and learning investments for PV modules with a progress ratio of 80%. The shaded area indicates remaining learning investments to reach the break-even point. The figure also shows changes in the break-even point for progress ratios of 78% and 82%



Source: (IEA 2000, Junginger *et al.* 2008).

3.4.2 Caveats and limitations of experience curves

Though the majority of commentators are broadly positive about the use of experience curves a variety of criticisms and caveats exist regarding their use, both in general and specific to the energy sector; indeed a few of the views are essentially sceptical.

Hall and Howell (1985), for example, undertook a critique of manufacturing/industrial experience curves and the benefits of learning-by-doing and argued that at the individual production plant level such learning is exhausted relatively early though, there may be continued learning at company level. It also examined other issues: the evidence that there is a common slope (learning rate) to experience curves; their usefulness for forecasting prices; and possible reasons for a spurious correlation between accumulated output and average cost. Hall and Howell concluded that experience curves appear in large part to reflect economies of scale (see also below on scale as an explanatory variable), and that they are of little practical value in forecasting or decision making.

Whilst this view is not representative of the bulk of the literature revealed through our review, it is worth bearing in mind the caution from Mukora *et al.* (2009) that experience curves show how costs may reduce over time, but provide no explanation of the reasons behind the cost reduction beyond its relationship (in the case of one-factor curves) to cumulative output. In essence, learning assessments chart outcomes but do not assess causation. Furthermore, it is also worth recalling the statistician's adage that 'correlation is not causation' i.e. there is no absolute imperative that cost reduction necessarily occurs following increased deployment or cumulative output – it could be coincidental, the result of other factors such as lower input costs or favourable currency movements.

In the sections below we examine further some of the main limitations and caveats regarding the use of experience curves.

Variable learning rates

Some analysts have questioned the assumption that learning rates remain constant over time given that a historical experience curve depicts the combined effect of many factors that are likely to have fluctuated over time and cumulative production. Only after many doublings of production, is there the possibility of discerning a clear trend (Mukora *et al.* 2009).

In the longer term the trend may be subject to fluctuation depending on the period examined and the stages of development a technology is passing through (Kromer 2010). In effect, it is argued that there is no absolute or unique learning rate for a given technology (Jamasb and Kohler 2007, Yu *et al.* 2011), that the learning rate may change over time depending on the data set considered (Ferioli and Van Der Zwaan 2009), and that the outcomes of scenario analyses such as the timing of future cost reductions is sensitive to small changes in learning rates (Nemet 2006).

Many commentators argue that costs tend to fall relatively swiftly during the innovation/ R&D phase and that in the absence of a subsequent radical discontinuity the learning rate will change to a lower level (i.e. lower cost reductions) when a technology enters the more mature phase of the commercial market (Junginger *et al.* 2008, Ferioli and Van Der Zwaan 2009). Moreover, in the early years of deployment, successive doublings of cumulative capacity are likely to be more easily achieved than in later, more mature stages, which could consequently make a better (i.e. higher) learning rate easier to achieve in the earlier compared to later years.

However, Soderholm and Sundqvist (2007) argue that one might expect to obtain lower learning rates in a full time series sample (including the earliest years) compared to a partial time series which only includes more recent years. This is because as a technology matures the degree of competition in the input factor markets becomes stronger and as a result prices fall - hence the relatively higher cost reduction rate for a partial, more recent data set (Söderholm and Sundqvist 2007).

Recent experience suggests that in fact competitive pressures can move costs in ways that are hard to predict, a point we return to in later chapters. Whilst the degree of competition to provide input factors to firms may well increase with greater deployment, the degree of competition to secure and consume those input factors is also likely to increase. There is therefore the potential (at least in the short term) for a supply chain squeeze, as was evident with PV silicon prices in the mid-2000s, onshore wind turbines in Germany during 1995-2001, and in the UK offshore wind sector (Junginger *et al.* 2008, Greenacre *et al.* 2010).

Thus, it is evident that learning rates are subject to considerable uncertainty, can be overwhelmed by other factors, can change depending on the period examined, and can do so for reasons which may be unclear or difficult to predict.

Absence of cost floors in experience curves

Some commentators caution that experience curve studies which do not include a cost floor in their extrapolated forecasts could result in excessively high cost reduction estimates (Alberth 2008). For all products or technologies a production or capacity limit is likely to exist due to market constraints.

If the market saturates, new capacity is only needed for the replacement of old, which limits the opportunities for learning-by-doing and cost reduction is likely to slow significantly or stop (Ferioli and Van Der Zwaan 2009). Additionally, energy technologies in particular may be constrained by the availability of natural resources and when resource constraints are reached the costs of the technology are likely to rise (Ferioli and Van Der Zwaan 2009). Some studies of renewable energy technologies have addressed this issue by imposing a floor to prevent the cost forecasts from becoming absurdly cheap (Kromer 2010), although doing so does then raise the question of how such a floor should be determined.

Deployment assumptions

Experience curves typically reflect cost changes relative to cumulative output and deployment. In order for an experience curve to estimate future cost levels at given moments in time, assumptions must be made about deployment rates over time. Such assumptions are inevitably subject to uncertainty and will be inaccurate to a lesser or greater degree. Experience curves cannot forecast whether and when actual market diffusion will occur and by what amount, and inaccurate deployment estimates will inevitably lead to inaccuracy in the level and timing of possible future cost reductions (Junginger *et al.* 2008).

Costs, prices, currency conversion and inflation

Ideally cost data should be used to formulate experience curves but production costs as opposed to market prices are often not available for obvious commercial reasons. Consequently, it is not uncommon for price data to be used instead when establishing historical learning rates and progress ratios. This contributes to the uncertainty in experience curves and makes it important to clarify the relationship between cost and price (IEA 2000, Kromer 2010).

Price data may be adapted to achieve an estimate of cost by removing a nominal percentage of normal profits. However, actual profit levels will tend to fluctuate as market and competition conditions vary. In addition, different phases of a technology or product's progress in the market may see the ratio of cost to profit vary quite significantly (Junginger *et al.* 2008). Currency conversions and corrections for inflation can also introduce errors into experience curve analysis, especially when analysing data from a country and period with a wide fluctuation in currency conversion rates and/or a high inflation rate (Schaeffer *et al.* 2004).

Inadequate, inappropriate, and absent data

Experience curves are based on historical cost (or price) data, but obtaining suitable and accurate data may be difficult (Sharp and Price 1990). As already discussed, for energy technologies that are still in an emergent phase, market experience and therefore data are inevitably limited. An example is provided by Mukora *et al.*(2009), commenting on the learning investment required to buy down costs in the nascent marine energy sector:

- Estimating the investment required to break even with conventional energy is highly sensitive to the initial costs chosen. A higher initial cost will increase the learning investment, number of deployments and time required to meet the break-even target. A robust estimation of initial cost is therefore essential.
- Choosing the level of cumulative capacity at which cost reduction begins is also important. Rather than cost reduction occurring from when the first prototypes are produced, it is likely that costs will remain constant or rise during the first phase of deployments. For example, in Denmark, significant cost reduction in wind power did not occur until a cumulative installed capacity of over 100MW had been achieved.
- At present there is limited evidence on the long-term learning rate for the technology. An analogy or proxy is sometimes made with established sector learning rates but this introduces considerable uncertainty and possible error.

A good example of the analogy problem was the formulation of experience curves to estimate future costs of UK offshore wind energy (see, for example, Chapman and Gross (2001)). Mukora *et al.* (2009) contend that having suitable data over sufficiently long time periods is a key issue for the use of experience curves. However, in the case of UK offshore wind, at least until the mid-2000s there was little primary data from which to construct such curves since the sector was still in relative infancy. One result of this was that early assessments of the future costs of offshore wind utilised learning rates borrowed from the onshore wind sector (Greenacre *et al.* 2010) despite the wide variation in onshore wind learning rates (McDonald and Schrattenholzer 2001) and the differences in costs breakdown between the onshore and offshore sectors (ODE Limited 2007, Blanco 2009, Feng *et al.* 2010). This is explored in more detail in the offshore wind case study.

Disproportionate influence of early trends

Data from pre- and early commercial phases in technology development may be uncertain and/or unrepresentative of subsequent trends and this can exercise significant and possibly disproportionate influence over experience curve trend analysis (Schaeffer *et al.* 2004). For many advanced technologies early cost estimates based on laboratory-scale projects and pilot plants are typically lower than the costs subsequently realised for early full-scale commercial plants. The reasons for such a cost increase, says Kromer (2010), are usually due to shortfalls in performance and reliability resulting from lack of experience, design flaws, or from unforeseen problems emerging during full-scale construction and commissioning.

System boundaries

The choice of system boundary may also make a difference to the value of a learning rate. Learning rates and experience curves originated at the corporate level but the system boundary has since been expanded to take in entire sectors, at a national, regional or global level, and the learning rates of each may vary. For example, whilst PV experience curves have almost exclusively been devised for globally produced modules, for wind turbines the majority of studies covers country-specific installed capacities (Junginger *et al.* 2008).

This could be of importance when learning rates based in e.g. a national system are used in global energy models. While country-specific experience curves may be suited to evaluate past local policy measures, they may not adequately measure the actual global rate of cost reduction of a technology at present (Neij *et al.* 2003). In addition, variations in physical conditions such as site location, and the choice of specific technology included within an experience curve system boundary, may also be important.

Input costs

Whilst historical experience curves data will include the effects of fluctuations in input costs such as raw materials, a number of studies, including for example Junginger (2008) and Greenacre (2010), note that experience curves used to extrapolate estimates of future costs cannot forecast future variability in input costs. This issue is particularly relevant to the experience of the major UK generating technologies in recent years where potential learning effects and other sources of cost reduction have been overwhelmed by ‘exogenous shocks’, especially in the form of commodity and fuel feedstock price increases. We return to this issue in Chapters 4 & 5 and the associated case studies.

3.4.3 Additional observations & issues for the experience curve paradigm

In addition to the potential limitations of experience curves, the literature also makes a number of observations that are nevertheless important to consider in an analysis of the experience curve paradigm. The most significant issues identified in the literature are as follows:

Compound systems

Energy generation technologies are compound in nature. Each technology is composed of multiple elements and hence its learning system is an aggregation of different sub-systems including product manufacture and generation performance (Neij *et al.* 2003, Junginger *et al.* 2008). These sub-systems are each affected by different learning and cost-reduction factors but an aggregated experience curve reflecting the system in total ignores information on sub-systems and their potential for evolution and cost reduction (Nemet 2006). For example, a wind turbine includes blades, generator, nacelle, tower and foundation. At this disaggregated level, each element has its own experience curve. Another learning system includes site acquisition and preparation, installation, and connection infrastructure. A further system relates to wind capture and generation including availability and efficiency (Ferioli and Van Der Zwaan 2009). Similarly in photovoltaic systems cost reductions in modules may occur more rapidly than those for installation or balance of systems components such as invertors.

In theory then, different learning systems could - and perhaps should - be disaggregated into multiple experience curves to give a more detailed and accurate picture of the trends involved. Often however, they are not, in great part because of problems of data collection, both in terms of work load and accessibility (Nemet 2006).

Application of experience curves to modular versus large-scale technologies

Based on empirical data, it appears that learning rates and the goodness-of-fit of experience curves depend on the technology considered. A more modular technology such as PV follows the historical trend closely - as does onshore wind - while larger scale plants (coal, gas and offshore wind) show greater fluctuations compared to the trend (Junginger *et al.* 2008).

Small-scale, modular PV has typically displayed a learning rate of about 20%. However with increasing generating plant size, learning rates seem to reduce and become less cost-beneficial. For example, (prior to the cost increases of recent years) onshore wind displayed learning rates of up to 15%, offshore wind had rates of around 10%, and pulverized coal plants about 8% (Junginger *et al.* 2008). This supports observations by Neij (1997, 1999) that there is an important distinction between power installations that require extensive construction in the field, and installations that can be mass-produced by centralised factories i.e. modular technologies learn faster and have greater cost reduction potential than large plant technologies. In addition, suggests Junginger, the greater variability and worse learning rates of larger scale plant arise from their often highly specific, custom-built nature. We return to these possibilities in Chapters 4 and 5.

Assumption of spillovers

Part of the theory of experience curves is an assumption that each firm in an industry will benefit from the learning-by-doing and experience of all firms – i.e. knowledge 'spillover' between firms. A similar idea is that of potential spillover from related technologies and industries. Learning rates that incorporate spillovers within clusters of technologies have been estimated and included in energy models (Alberth 2008). However, the reality is that firms will typically try to defend their intellectual property and commercial advantage (Nemet 2006). The assumption of significant benefits from spillovers may therefore be over-optimistic.

Modifications and extensions of the one-factor experience curve model

In order to address some of the limitations of the traditional experience curve, some attempts have been made to refine or improve upon the basic one-factor learning-by-doing model. Jensen (2004), for example, proposes that weighted averages for the input data be used in order to obtain a better model of technological development.

Meanwhile, Pan & Kohler (2007) suggest a logistic curve approach. Here, life cycle theory is adopted to explain technological changes and to integrate the growth rate and R&D investment into the experience curve model, in order to find an expression for the scale of technological change. This logistic curve model incorporates all phases of technology development as used in life cycle theory. It also describes the life span of energy technology in the long run. However, whilst the proposed logistic curve would include the growth rate and R&D investment as the driving variables, it would not include scale effects and changes in input prices since Pan & Kohler (2007) suggest that too little is known about them.

Arguably the most significant refinement suggested by several commentators is to use a covariate analysis model where the simple curve with only one explanatory variable is extended to include additional variables. As already noted, cost (or price) reduction has most typically been considered as a variable dependent only on cumulative production or deployment – the proxy for learning-by-doing. This is generally described as a 'single or one-factor experience curve' (SFEC). However, one of the most important criticisms of typical experience curve analysis has been the neglect of several parameters (i.e. other explanatory variables) that also impact on cost (Neij *et al.* 2003, Pan and Köhler 2007, Yu *et al.* 2011). Jamasb

(2007) argues that the consequence of this neglect and of reliance on simple learning-by-doing curves is to overstate the effect of cumulative production or deployment, especially for emerging technologies, and therefore to produce inaccurate estimates of learning rates.

Some commentators therefore argue that each source of cost reduction must be analysed separately (Neij 2008) and thus propose the inclusion of one or more additional explanatory variables to produce so-called 'two-factor' and even 'multi-factor' experience curves (TFECs and MFECs). Yu (2011), for example, contends that using a TFEC incorporating learning-by-doing and learning-by-researching still does not satisfactorily explain cost reduction, and in addition, scale effects and input price effects should be incorporated into the model. Junginger (2006), on the other hand, cautions that whilst these approaches may yield a more accurate estimation of past and future cost reductions, it also requires detailed data, which may not be available. Nevertheless, the intention is that such two-factor or multi-factor experience curves would describe more of the systematic variation (Jensen 2004).

Here we consider each of the main additional explanatory variables in turn:

Learning-by-researching as an explanatory variable

The experience curve model has sometimes been extended to include "learning-by-researching" whereby R&D leads to technical progress and cost reduction. This learning effect may be accounted for in two-factor curves by incorporating cumulative R&D spending or the number of patents as proxies for the stock of knowledge (Jamasb and Kohler 2007, Kahouli-Brahmi 2008, Mukora *et al.* 2009).

Learning-by-researching rates have been estimated for several energy technologies and, despite the variability, a causal relationship between R&D and cost reduction can be inferred (Kahouli-Brahmi 2008). In support of the idea of two-factor curves, Jamasb (2007) compares electricity generation learning-by-doing rates for single factor curves based only on cumulative output with learning-by-doing rates in two factor curves which also include learning-by-research. The results, in Table 3.1 below, show that there are considerable learning-by-doing rate differences between single and two-factor curves, and that single-factor learning curves overestimate the effect of learning-by-doing in general and that of new and emerging technologies in particular (i.e. the significant effect of learning-by-researching is not taken into account).

Table 3.1 Learning by Doing Rates Using Two or Single-factor Curves

Technology	Learning By Doing Rate – Two-Factor Curves	Learning by Doing Rate – Single-Factor Curves
Pulverized fuel supercritical coal	3.75%	4.8%
Coal conventional technology	13.39%	15.1%
Lignite conventional technology	5.67%	7.8%
Combined cycle gas turbines (1980-89)	2.20%	2.8%
Combined cycle gas turbines (1990-98)	0.65%	3.3%
Large hydro	1.96%	2.9%
Combined heat and power	0.23%	2.1%
Small hydro	0.48%	2.8%
Waste to electricity	41.5%	57.9%
Nuclear light water reactor	37.6%	53.2%
Wind - onshore	13.1%	15.7%
Solar thermal power	2.2%	22.5%
Wind – offshore	1.0%	8.3%

Source: (Jamasb and Kohler 2007)

Indeed, in some cases, the effect of learning-by-research may be more significant than that of learning-by-doing (Jamasb and Kohler 2007). Pan & Kohler (2007), for example, argue that in the case of wind power, the fundamental cost factor is the turbine and that this depends more on innovative design than cumulative deployment. This issue has possible policy implications in terms of the relative importance of policies to expand capacity and investment in R&D (Jamasb and Kohler 2007).

In their 2007 paper, Pan & Kohler go on to argue that the extended two-factor curve is an improvement on the conventional experience curve but acknowledge that this approach is not yet widely used. They suggest that this is because whilst the approach provides a potentially better fit for the innovation stage it cannot capture well the 'learning-by-continuous research' that takes place in the later stages of deployment. Further notes of caution come from Kobos (2006) who raises the concern that obtaining the R&D data required to construct two-factor curves may be difficult, as well as Ferioli and Zwaan (2009) who note that distinguishing the effects of R&D versus deployment can be problematic, and Mukora *et al.* (2009) who suggest that it is still too early to establish whether two-factor curves will provide a sound model.

Scale as an explanatory variable

Economies of scale, as distinct and separate from learning effects are another explanatory variable proposed for multi-factor experience curves (Sharp and Price 1990). Most studies treat scale effects as an inherent part of the experience curve and do not disaggregate it but its absence as a distinct factor may have an impact on the accuracy of learning rates (Söderholm and Sundqvist 2007, Kahouli-Brahmi 2008). In earlier work Hall and Howell (1985), suggested that cost reductions may be just as closely correlated with the current scale of production as they are with accumulated output to date, which if correct, would suggest that cost reductions in the later years of a technology may be driven by economies of scale effects rather than long-term learning effects.

Whether scale economies should be treated as distinct from or included in an aggregated experience curve for energy cost purposes is still open to question since, in the energy arena, relatively few studies have attempted to separate learning effects from returns to scale effects, but see Isoard and Soria (2001) and Yu *et al.* (2011). Other notable exceptions include Söderholm and Sundqvist (2007) who argue that by not incorporating positive returns to scale in the field of nuclear generation, too large a share of cost reductions may be attributed to learning effects, and Nemet (2006) who stresses the contribution of economies of scale in manufacture to the cost reductions of PV modules.

Influence of policy as an explanatory variable

Most experience curve studies assume the structure of the model is unaffected by policy changes that take place during the period being studied. However, Soderholm and Sundqvist (2007) propose that policy measures such as feed-in tariffs should be assessed to determine to what extent they are an 'omitted variable', suggesting for example that fixed feed-in tariffs may reduce the incentive for innovation (and therefore have an influence on the speed of cost reductions).

With regard to policy support manifested through publicly funded R&D activities, Junginger *et al.* (2008) suggest that there is no clear evidence that such policy can directly influence cost reductions, whereas they do acknowledge that policy aimed at driving deployment and market size can influence the trajectory of cost reductions.

Competition as an explanatory variable

As noted earlier, Soderholm and Sundqvist (2007) argue that as a technology matures, competition in the input factor markets is likely to become stronger and therefore prices should fall as a result. Supporting this proposition, Greaker and Lund Sagen (2008) found that competition was the most significant factor in their study of the falling cost trend for LNG liquefaction plant.

Time as an explanatory variable

A paper by Ferioli and Zwaan (2009) argues that accounting for time itself would improve the understanding and use of experience curves, and that the time dimension may therefore need to be reintroduced into analyses of costs and future estimation. The argument is based on several points including: the observation that 'experience' as measured by cumulative production or deployment should not be the only explanatory variable; that a good fit of cost-capacity data does not necessarily imply a constant learning rate; and that learning rates may vary over time and are sometimes negatively affected by subsidies (as discussed previously, it is argued that they may distort incentives to innovate).

Influence of different explanatory variables at different stages

To conclude the above review of potential explanatory variables additional to cumulative output or deployment, we note the contention that different variables may take material effect at different stages in the developmental progress of a product or technology.

An example is provided by Yu's (2011) research into solar PV technology development which favours a multi-factor approach. Here, the results suggest that at the technology's emerging stage, the learning-by-doing effect plays a minor role in cost reduction. Nor do economies of scale take place at this stage. The factors that have driven the cost decline are input prices (primarily silicon) and other factors such as learning-by-researching and subsidies from government. At the diffusion stage, economies of scale start to play a minor role in cost reduction, as does learning-by-doing, whilst input prices and the other factors still play an important role. Finally, at the mature stage, learning-by-doing and the returns to scale effect instead of input prices and other factors contribute most to cost reduction.

Building on this idea, analysis by Kahouli-Brahmi (2009) indicates that:

- In the early stages, emerging technologies exhibit low learning rates associated with scale effects because diffusion barriers and uncertainty cause diseconomies of scale;
- Evolving technologies show high learning-by-doing and learning-by-researching rates because they respond quickly to capacity expansion and R&D activity;
- The conventional technologies, now in their mature phase, display low learning rates but increasing returns to scale.

3.4.4 Principal conclusions on the use of learning rates

Reliable and disaggregated data
Learning rates need to be based on reliable data, preferably of cost not price if possible. In addition, given that energy generation technologies are comprised of several main components or sub-systems, a more accurate picture is likely to emerge if the system is disaggregated to provide data for separate component experience curves. It appears that the use of 'proxy' data from different technologies, however analogous or similar they may appear, should also be treated with considerable caution.

Use of error margins
In particular for long-term forecasts, even relatively minor variations in learning rates can lead to significantly deviating cost estimates. Junginger (2008) therefore recommends calculating error margins in learning rates in order to provide a range of future cost scenarios.

Span of cumulative output and duration of period
To obtain a reliable extrapolation of future estimated costs, Ferioli (2009) suggests that cost data should span several orders of magnitude of cumulative output. Inadequate data series might not be enough to reveal important trends or discontinuities, or the presence of non-learning sub-components (which become an increasing share of total cost and ultimately lead compound system learning rates to decline).

The issue of what constitutes a sufficient level of data can also be addressed in terms of time. In order to get learning and deployment rates for forecasting purposes, Schaeffer *et al.* (2004) argues that a period of at least ten years' worth of historical data should be available. This is particularly applicable to cases where price data is being used not cost data in order that sufficient time is allowed for price trends to be reliably reflective of cost trends.

In addition, Schaeffer *et al.* (2004) recommends that attention should be paid to the effects of industry cost/price cycles. Typically, a cycle alternates between periods of relative price stability and 'shake-out' periods of steep decline (or, more rarely, of increase). If the period on which a progress ratio is based includes an over-representation of one type of phase, then the resultant progress ratio could be too optimistic (if a price decline phase is over-emphasised) or too pessimistic (if a stability phase is over-emphasised).

Whilst Schaeffer *et al.* (2004) argues that the data period from which a learning rate is derived should not be too short, Neij (2008) proposes that the forecast period emanating from it should also not be too long. Neij notes that experience curves may be used to forecast cost development as much as 50 years ahead. However, Neij argues, this may not be appropriate since the experience curve is a trend analysis tool only suitable for the analysis of established technologies with forecasts of mid-time ranges under conditions of low uncertainty and for a series of incremental innovations. In addition, the Schaeffer *et al.* (2004) study of PV forecasts demonstrates that the further into the future an estimate is based, the more inaccurate it is likely to be.

Correct system boundaries
Analysing only parts of a learning system may provide misleading results and deviations in the learning rate (Junginger *et al.* 2008). The potential for cost reduction can be measured within different geographical boundaries – for example, at regional, national, European, or global scale. However, the rate and range of learning and cost reduction may depend on the extent to which a technological development is bound to a specific geographical area. Differing physical environments may also be important, as is the case with on and offshore wind such that the use of data in a 'related' sector (i.e. onshore wind) may prove misleading.

Experience curves and engineering assessment are complementary approaches for forecasting cost trajectories but each must be used in full awareness of the limitations of the other.

Acknowledgment of uncertainty and assessment of deviation from projections

According to Nemet (2009) two important requirements are indicated:

- Policy makers more explicitly consider uncertainty in cost projections
- Better tools are needed to identify the significance of near-term deviations from cost projections.

Nemet proposes that given the considerable variation in rates of technological improvement over time, policy makers should consider learning as a stochastic process; that is, that aspects of the process will remain unpredictable. Thus, if policy makers are to rely on cost projections derived from experience curves, they should be explicit about the reliability of predictions and policy decisions should be made acknowledging the observed variation in learning rates.

In addition, Nemet (2009) argues that devising ex ante methods to identify the significance of near-term deviations in cost and performance trends is essential. Trend deviations make policy more difficult. It can be hard to identify whether a deviation is due to a short-term supply squeeze or a longer term limit on cost reduction. One promising development, reports Nemet, is the inclusion of explicit treatment of learning uncertainty in modelling.

3.5 Overall conclusions

It is clear from the literature reviewed that whilst there are two principal methodologies for forecasting energy cost trajectories, the subject is nonetheless complex, the details often contested, and neither of the two approaches, their various refinements and modifications are without uncertainties and difficulties. Nevertheless, both approaches have demonstrated usefulness and indeed both are widely used.

With regard to experience curves, Jamasb (2007) points out that the strongest reason for applying them is not that the various issues and drawbacks associated with them have been – or will be – resolved but rather that, caveats notwithstanding, the evidence for some degree of experience-based cost reduction is overwhelming. Thus "learning rates are valid but incomplete data, which need to be better explored, but not ignored, in economic analyses of technology" (Jamasb and Kohler 2007).

In the case of the early years of emerging technology deployment (i.e. in the absence of sufficient cost and capacity data) a greater reliance on engineering assessment would appear to be the more appropriate approach. Once a track record has been established – which is likely to take several years – then the use of experience curves becomes more appropriate. Yet engineering assessment is also subject to limitations and caveats abound.

Overall there is no tension between experience curves and engineering assessment. The approaches complement one another, but both must be utilised in full awareness of the limitations of the other.

Whilst learning assessment is in itself complex and fraught with difficulties, learning may be overwhelmed by other factors such as exogenous cost shocks. These exogenous factors and other reasons – both methodological and endogenous – for discrepancies between cost expectations and reality, are explored in more depth in Chapters 4 and 5 and the associated case studies.

4. Generation costs case studies

4.1 Introduction

This chapter summarises the findings of six case studies which examine the cost forecasts and 'cost out-turns[9]' of different electricity generation technologies, covering a variety of technological maturity, cost profiles and operating characteristics. The case studies are based on targeted systematic reviews of the evidence base for the cost trajectories of each technology, the results of which were documented in working papers that can be found on the UKERC web pages[10].

The case studies covered nuclear power, combined cycle gas turbine (CCGT), coal and gas-fired carbon capture and storage (CCS), solar photovoltaics (PV), and onshore and offshore wind generation plant. Across the six case studies, the project team collated over two and half thousand data points and a detailed analysis of this data can be found in the working papers.

Data has been collected for historical cost estimates (i.e. estimates for notional plants built at the time the estimate was made) and cost forecasts (i.e. estimates for notional plants to be built at some point in the future). There are of course time dimensions to both these types of estimates. In the case of historical estimates the time dimension will reflect the year the estimate was made, and in the case of cost forecasts there are two time dimensions with the first dimension being the year the forecast is made, and the second being the point in the future that the forecast applies to. This allows us to derive insights into how views of future technology costs have evolved over time. The sections that follow summarise the evolution of cost forecasts by presenting estimates from pre- and post-2005.

Each of the technologies is examined in turn, briefly summarising the findings of the case studies and discussing the key issues and trends that the reviews identity. The overall findings and themes which emerge from the case studies are explored in detail in the Chapter 5.

4.2 Nuclear

Introduction

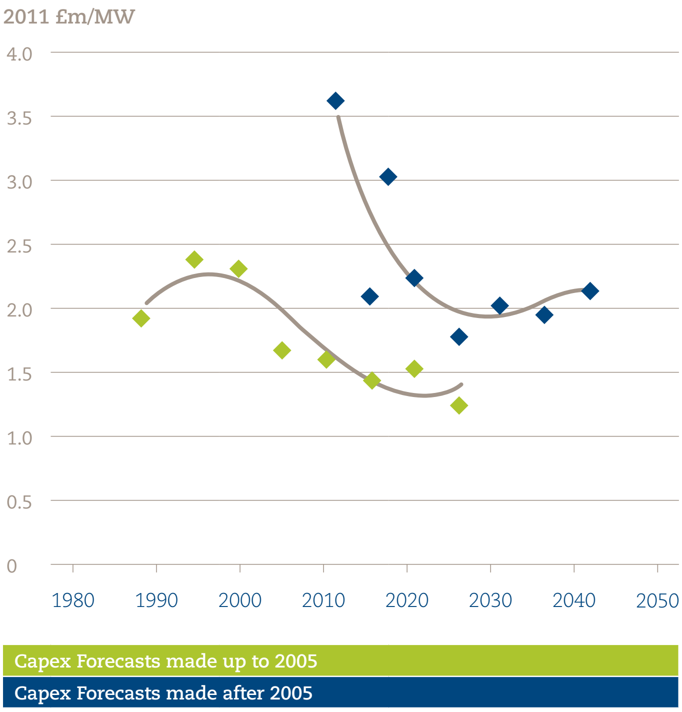
Approximately 75 academic articles and grey literature reports were reviewed for the nuclear case study (Greenacre 2012a). The analysis focuses predominantly on capital rather than levelised costs. In part, this is because there is more data on capex in the evidence reviewed, and also because capital costs account for the majority (60 to more than 75%) of the levelised costs of nuclear energy generation (MacKerron *et al.* 2006, Grimston 2012b).

Forecasts of future nuclear costs have been derived mainly from engineering/technical assessment rather than from experience curves. This is perhaps unsurprising since much of the track record is characterised by rising and/or highly variable costs, rendering learning rates either negative or at least very uncertain. By contrast, engineering assessment of potential future cost trends is less strictly bound by past history. For contemporary cost out-turns, the evidence revealed in the review tends not to be confirmed data from utility companies or reactor vendors. Instead they are estimates from academic and governmental analysts and other nuclear industry observers. The reasons for this include commercial sensitivities and a relative lack of 'real world' projects in OECD countries in recent years from which to extract data.

Cost forecasts

Figure 4.1 below presents a summary of worldwide capex future forecasts between the late 1980s and the early 2040s for all reactor types. It shows the in-year average forecast costs for two groups, one consisting of forecasts made up to 2005, the other consisting of forecasts made from 2005 onwards. The year 2005 was chosen because the mid-2000s appears to have been a pivotal time when estimates of contemporary costs began to rise significantly from a plateau low.

Figure 4.1: In-year means of nuclear forecast capex values worldwide, comparing pre and post 2005 estimates



Source: (Greenacre 2012a)

[9] The term 'cost out-turns' is used here to describe values for a given technology which were intended to represent a view on what the actual current costs of that technology were, at the time the estimate was made. It is important to note that due to commercial sensitivities such values generally represent estimates based on the then current knowledge of generalised technology cost and characteristics, rather than data from specific projects.

[10] www.ukerc.ac.uk/support/tiki-index.php?page_ref_id=2863

Figure 4.1 demonstrates how nuclear capital costs have in the past been expected to fall over time, and how they are still expected to do so, albeit from a higher starting point averaging over £3.5m/MW in 2010. In the mid-2000s, cost forecasts for the relatively near future were revised significantly upwards to reflect a new reality of rising contemporary cost estimates, driven by design changes, commodity prices movements and a wide range of other factors. However, costs are still expected to fall in the longer term, though to a level at least £500,000/MW higher than expected by the earlier pre-2005 forecasts.

Turning to recent forecasts specific to the UK, there are divergent opinions regarding future capital costs. The more optimistic forecasts make the judgement that significant cost reductions will occur by the mid-2020s, effectively through various forms of learning as technologies progress from 'first of a kind' to 'nth of a kind' (Mott MacDonald 2011). For example, a 25% reduction in overnight costs from approximately £3.6m/MW to £3m/MW by 2025, or even down to £2-2.5m/MW by 2020 and to £1.6-2.45m/MW in 2040 assuming that a currently assumed £0.7m/MW 'congestion premium' is eliminated (Mott MacDonald 2011). By contrast, more pessimistic observers tend to place greater emphasis on the historical experience of costs rising during construction (Grubler 2009).

Since capital costs are such a dominant component of total costs for nuclear power, analyses of levelised cost projections and forecasts are generally closely aligned with that of capital costs. Forecast reductions in levelised costs are therefore predicated principally on reductions in capital costs rather than substantial improvements in others areas such as increased plant lifetime or improved load factor.

In the case of plant lifetime, this is because the discounting effect of the levelisation formula (see Chapter 2) means that adding or subtracting output which will occur several decades in the future has a relatively small impact on levelised costs. For example, reducing the assumed plant load factor of 60 years used in Mott MacDonald (2010) to the 40 years used in Harris *et al.* (2012) increases levelised cost by less than 2%.

In principle, varying the assumed load factor of a nuclear plant can have a more significant impact than varying the plant lifetime, with an increase in assumed load factor from 80% to 90%, resulting in a decrease of up to 10% in levelised cost (IEA 2010a). However, the opportunity for future overall cost reductions from this area is limited because the load factors typically assumed for notional new plant already represent close to the best that have been achieved by the industry historically, and are approaching the practical maximum achievable once periods of unavailability for maintenance are allowed for (Mott MacDonald 2010, Harris *et al.* 2012).

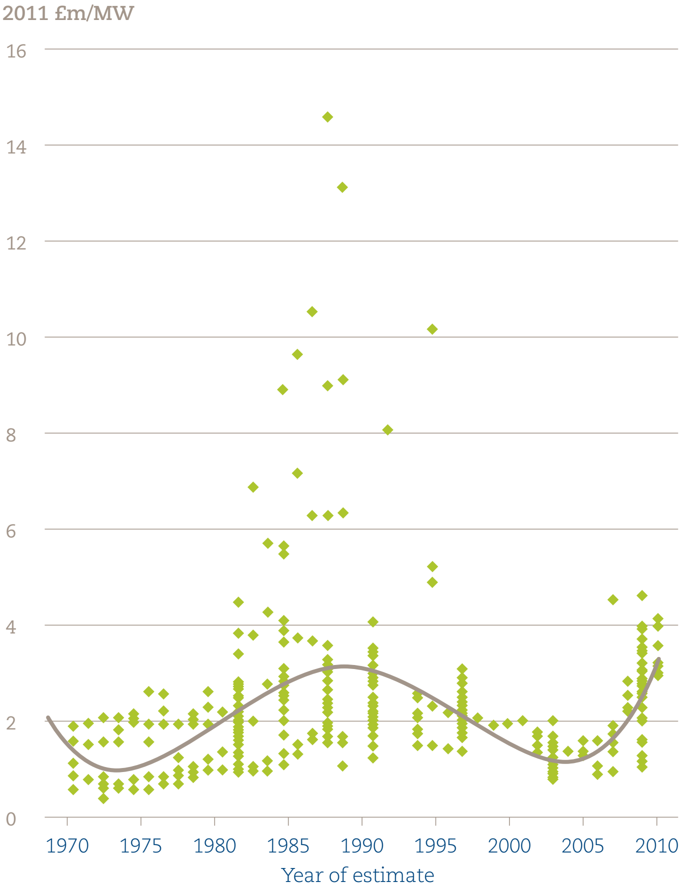
Nevertheless, some analyses suggest that levelised costs will fall in the future, from a central figure for 2010 of around £95/MWh (Mott MacDonald 2010) to around £65/MWh for a project with a notional mid-2020s completion date (Parsons Brinckerhoff 2011). Longer term reductions were envisaged in (Mott MacDonald 2011) which assumed a current levelised cost of £89/MWh reducing to £63/MWh and £50/MWh for 2020 and 2040 respectively (using a central discount rate projection and assuming the removal of the congestion premium). Some analysts are not as optimistic, and raise concerns in particular over the potential for capital cost escalation during the pre-construction and construction phases, which would lead to substantially higher levelised costs (Harris *et al.* 2012). What is clear from all the analyses is the paramount importance of achieving capital cost reductions if lower levelised costs are to be realised at some point in the future.

Cost out-turns

Here, we consider cost out-turns over the last four decades and how this data compares with what was projected. From the outset, the history of nuclear costs has been characterised by some significant disparities between expectations and reality. A paper by Cooper (2009) provided insight into the early years of commercialised nuclear power in the US, with the analysis suggesting that not only were both cost projections and out-turns increasing from the mid-1960s to the mid-1970s, but also that actual costs were increasing at a faster rate than projections. Hence, both capital cost containment and forecast accuracy deteriorated over the period.

Figure 4.2 presents worldwide contemporary capex estimates between 1972 and 2011, drawn from the sources identified by the case study. From the early 1970s costs rose gradually before a sharp escalation in the early 1980s which peaked around the late 1980s and early 1990s. Comparing Figure 4.1 and Figure 4.2, for a period of time between the late 1980s and the mid-2000s forecasts were broadly correct in identifying an upward trend of contemporary costs followed by a downward trend.

Figure 4.2: Range of estimated nuclear contemporary capital costs worldwide over last four decades



Source: (Greenacre 2012a)[11]

Nevertheless, the forecasts significantly part company with estimated outcomes in two ways: i) against expectations, the contemporary cost trend turned sharply back up in the second half of the 2000s; and ii) throughout the period examined cost out-turns (as opposed to the shape of the trend) have been considerably higher than originally anticipated.

Turning to out-turns during the last decade or so, the evidence shows that the estimated costs for nuclear new build between 2000 and 2010 have for the most part gone up, in some cases by more than 100% to over £4m/MW. In 2004 estimated capital costs for nuclear new build in the US were under £1m/MW and subsequent plants were expected to have even lower capital costs. However, by the second half of the decade, costs had increased considerably with one 2007 report estimating cost out-turns of between £1.8m/MW and £2m/MW for a new nuclear plant (Grimston 2012b). Meanwhile, also in 2007, Florida Power and Light estimated the total cost of one of its proposed project as being between £2.75m/MW and £4m/MW.

In Europe, the Olkiluoto project in Finland had been expected to cost under £1.8m/MW and to be completed in May 2009 but by 2010 was running three years behind schedule with projected final costs of £2.6m/MW. The project is still under construction at the time of writing (summer 2013). In France meanwhile, the costs of the Flamanville reactor were restated at £1.9m/MW in 2008, up more than 17% from a year earlier (Grimston 2012b)[12]. Between 2008 and 2010 the estimates of nuclear generation costs in the UK have risen by 40% (Parsons Brinckerhoff 2010).

Main cost drivers and themes emerging from Nuclear case study

In broad terms, nuclear costs rose until around 1990, seemingly declined until the early to mid-2000s, and then started to escalate again. Each of these periods is characterised by a variety of competing drivers, some forcing costs up, others down.

During the 1960s to 1980s, environmental & safety concerns fostered a regulatory climate in which the rules for nuclear design, build, and operation kept changing thereby causing project times to overrun and costs to escalate (see, for example, Cantor and Hewlett (1988), MacKerron (1992), Hultman *et al.* (2007), Neij (2008), Rai *et al.* (2010)).

Serious nuclear incidents and accidents during this period – the 1975 Browns Ferry and the 1979 Three Mile Island (TMI) incidents, and the 1986 Chernobyl accident – increased the uncertainty and upward pressure on nuclear costs (Grubler 2010, Grimston 2012b). NEA (2000) observes that US plants built before 1979 took an average of five years to build and license whilst those built post-Three Mile Island averaged almost 12 years. In the latter cases, financing and other time-related cost escalations could represent as much as half the total cost (Spangler 1983, NEA 2000). According to Cohen (1990), the increase in US construction time from 7 years in 1971 to 12 years in 1980, plus the increase in labour and materials costs, contributed to a quadrupling of capital costs.

From the 1980s, when the designs perceived as safe had become established, a more stable regulatory climate prevailed. Yet despite this, reactor design and related systems continued to become more complex and costs continued to escalate (Grubler 2010). Continuing design change due to commercial considerations as well as regulatory pressures, resulted in a lack of standardisation, over-complexity, and consequent diseconomies of scale (Cantor and Hewlett 1988, MacKerron 1992, Rai *et al.* 2010). Moreover, the ongoing changes and increasing complexity compromised the learning effects that were expected over time.

[11]Note that all the outlier data points above £6m/MW originate from a single source (Grubler 2009) and apply only to US reactors. It would appear that these cost estimates reflect especially long construction times giving rise to greater overnight and (especially) higher financing costs.

[12]Note that $ and € amounts have been converted from the original source to £ using bank of England historical exchange rates data.

Other factors that drove up costs during the 1960s to 1980s were the rising costs of labour and the cost of capital. The economics of nuclear power were impacted by high interest rates prevailing at the time, especially when construction schedules were also subject to significant delays (Spangler 1983). In addition, the evidence reviewed suggests that appraisal optimism and deliberate cost under-estimation also contributed to the disparity between future cost forecasts and actual out-turns.

During the 1990s to mid-2000s, almost all the nuclear construction activity was occurring in South America, Eastern Europe and Asia rather than the developed countries of North America, Western Europe, and Japan. Regarding the drivers of cost reduction in the developing countries, Grimston (2012a) points to a combination of:

- lower input costs[13], in part due to a slowing down of the world economy;
- less cost-forcing regulatory pressures;
- a greater incidence of command-and-control type economies likely to ensure stable electricity prices which therefore lowered the risk premium on financing.

Construction times also played an important role. Tolley and Jones (2004) observe that the nuclear plants in construction since the early 1990s – mostly Asian – were built in shorter construction times than in the US and even in France, and with less cost variability. Up to the late 1970s when the last US plant began construction, the average construction time in the US was nearly ten years. For plants beginning construction between 1993 and 2001, the global average was just over five years.

Significantly, the contemporary cost estimates originating from the developed countries were also coming down even though no actual construction was taking place. It is likely that these estimates of cost were being influenced in part by the numbers emerging from the lower cost environments where construction was actually taking place (Grimston 2012a).

For the period from the mid-2000s onwards, and notwithstanding the 2008/2009 financial crisis and ensuing recession, increased estimated costs can be attributed in large part to worldwide competition for resources and commodities (such as steel and cement) and for manufacturing capacity (Schlissel and Biewald 2008, Grimston 2012b). Strong demand for generation plant has resulted in cost increases, supply chain issues and longer delivery times as manufacturers have struggled to meet demand. Nuclear plant operators have also been competing with oil, petrochemical and steel companies for access to resources (Grimston 2012b). Other possible cost drivers include skills shortages, greater price transparency for new nuclear build, and a more realistic estimation of costs in the light of the recent experiences in Finland and France.

Several dominant findings and themes emerge from the nuclear case study's analysis of costs trajectories and of the comparisons between expectation and reality. These are summarised below.

First, notwithstanding some dissent, it is evident that appraisal optimism has been a fairly consistent feature of nuclear costs analysis. Estimates have typically not reflected the range of uncertainties, and have used inadequate contingencies given nuclear's history of regulatory instability, as well as technical and construction difficulties. In addition, the importance of location and technology specificity has been undervalued, with insufficient weight given to the challenges presented by a profusion of different reactor types and sizes (MacKerron 1992, Rai *et al.* 2010).

Second, the global cost profile over the last five decades makes it difficult to justify the application of the experience curve method of future cost projection. Given the profile's volatility, choosing a limited time frame in which to measure cost change against installed capacity would be arbitrary, but if nuclear energy's entire history were chosen the learning rate would be highly uncertain but definitely negative.

The potential for learning effects to be overwhelmed by other cost drivers or even to be reversed and become 'negative' has a range of explanations. The literature suggests two reasons for 'negative learning'. First, reactor and project scale-up has led to disproportionately cost-increasing complexity and resultant increases in construction times and component and labour costs. This might perhaps be described as 'unlearning-by-doing at too large and complicated a scale'. Secondly, despite build elsewhere in the world, long gaps between isolated individual country projects may result in 'organisational forgetting' or 'knowledge depreciation' thereby compromising project management. "If construction is sporadic, learning effects will suffer" (Tolley and Jones 2004).

Even if not negative, the learning effect can still be compromised or overwhelmed by a variety of cost-increasing factors. Regulatory instability can force design changes and even back-fitting leading to higher overnight costs, construction delays, and additional financing charges. It can also exacerbate financier uncertainty and increase possible funding rates.

In large part, the regulatory issues reflect the fact that nuclear power is in a different safety category than other generating technologies. The accidents at Three Mile Island and Chernobyl demonstrate that nuclear energy is especially vulnerable to cost shocks when there are doubts about its safety. Indeed, Schneider *et al.* (2011) report that the rating agency Moody's has estimated the Fukushima accident will likely result in a range of higher

[13]The cost of labour is a major factor for nuclear projects, far outweighing the cost of the basic raw materials. Mott MacDonald (2011) estimated that only around 4-5% of total nuclear capex was attributable to the raw materials, whilst 'two thirds of the capex is accounted for by labour, supervision and project management services'. This will clearly have important implications for projects undertaken in regions with relatively high labour costs. We return to the impact of labour costs in Chapter 5.

costs as a result of increased scrutiny, more stringent safety procedures, and longer maintenance outages.

A further intrinsic aspect of nuclear energy is that it tends to be very large-scale and site-specific and cannot easily benefit from mass production economies of scale in the way that, for example, PV or wind turbines can. Economies of unit scale may well be offset by growing complexity, whilst opportunities to benefit from multiple unit construction at the same site may be infrequent.

Lack of economies of scale have been exacerbated by too little standardisation. Despite the relatively small number of basic reactor designs, numerous variants have been tried over the years, undermining learning opportunities and increasing the likelihood of construction and operating problems. Indeed, Tolley and Jones (2004) suggest that perhaps the greatest potential for cost reduction lies in utilising standardised designs and (if possible) constructing plants in series.

The nuclear example also suggests that there can be occasions when excessively fast roll-out may compromise the ability to incorporate learning into successive units (MacKerron 1992, Rai *et al.* 2010). In addition, growth in deployment typically leads to increased competition for raw materials, components, and skills, and thus potential commodity squeezes and supply chain bottlenecks. In the case of nuclear, there are sometimes only one or two suppliers for critical parts and nuclear projects also have to compete globally with other major construction projects for key commodities (Schlissel and Biewald 2008, Grimston 2012b).

Specifically in the UK, Cogent's (2010) report warned that a new build programme may have potentially seven reactors under construction at the same time during the early 2020s. During this same period India and China will, by themselves, be increasing current global nuclear construction rates by around 60%. This may well place further pressure on supply chains, increase construction costs and jeopardise timing plans. Again, we explore the theme of supply chain and market dynamics in greater detail in the following chapter.

4.3 Combined cycle gas turbine (CCGT)

Introduction

More than 50 pieces of evidence comprising both academic journal papers, as well as government and industry reports were reviewed for the CCGT case study (Castillo Castillo 2012). Cost forecasting has typically been the domain of energy research institutes, government analysts, and consultants. Engineering firms involved in CCGT construction appear to be cautious about forecasting and have instead tended only to provide non-attributable estimated cost out-turns. Cost out-turns are more abundant than forecasts within the literature reviewed (Ibid.).

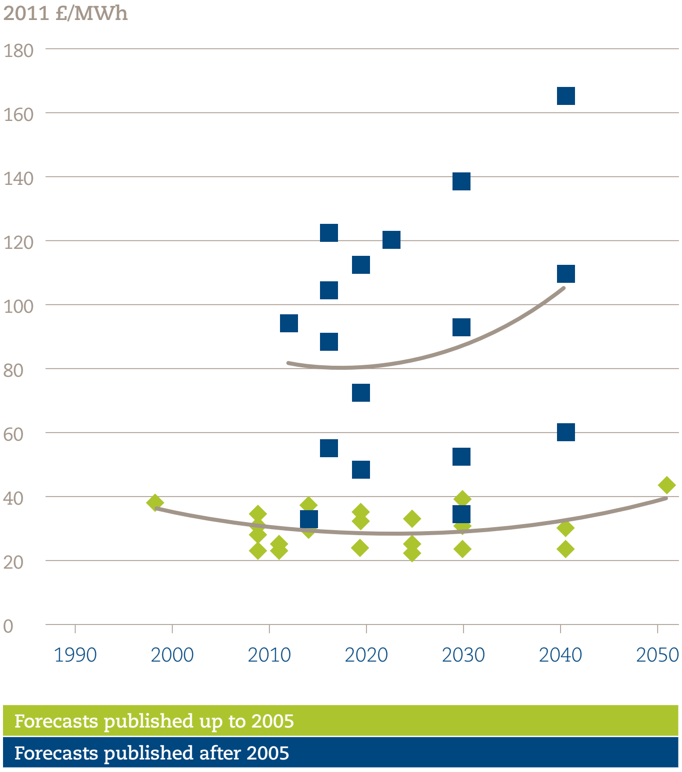
An important feature of the data reported in the literature is that, despite the variability and dominance of fuel costs in the levelised cost of electricity (LCOE), forecasts and contemporary cost estimates are often not reported in comparable capital expenditure terms but as levelised costs. This makes it difficult to evaluate 'learning' effects such as improved efficiency or reduced construction costs independently from fuel price impacts (Ibid.).

Cost forecasts

Fuel is the dominant CCGT cost component and can constitute between 60% to 80% of the LCOE, and an even greater share in some cases (IEA 2007). Consequently, it is fuel costs that have shaped the two main trends in forecasts (IEA 2005, IEA 2007, Mott MacDonald 2010). The case study's analysis of worldwide forecast data together with the trajectory of gas prices over the past 15 years identifies the end of 2005 as a transition point from relatively constant cost forecasts to much less optimistic ones.

Figure 4.3 shows the two trends and the markedly higher variability in post-2005 forecasts due to the widespread inclusion of (methodologically and geographically varied) gas price volatility calculations. For example, gas prices for the US and UK markets started increasing significantly at the turn of the century with particularly pronounced spike-rises at the end of 2005 and the beginning of 2008 to levels up to 600% the typical values of the 1990s (Alterman 2012).

Figure 4.3: Range of international forecasts of LCOE for CCGT up to and post-2005



Source: (Castillo Castillo 2012)

Figure 4.3 shows how pre-2005 forecasts proposed stable costs within the range of £25 - £41/MWh up to 2050 suggesting that technical advances leading to efficiency gains, and any exogenous upward cost pressures would cancel each other out. By contrast, post-2005 forecasts feature a much wider spread and include significantly higher projections, for example up to £115/MWh by 2020, reflecting a more complex set of influencing factors and more varied assumptions associated with each factor (Castillo Castillo 2012).

Gas (fuel) price increases are of course the principal driver of the increases in the estimates. However other factors are also noted in the literature. For instance, it is also argued that greenhouse gas emission abatement in European policy has reinforced the upward trend and introduced further uncertain variables (Parsons Brinckerhoff 2010). With respect to projections for 2050, assumptions over generation mix and load factors become significant considerations (Timera Energy 2011).

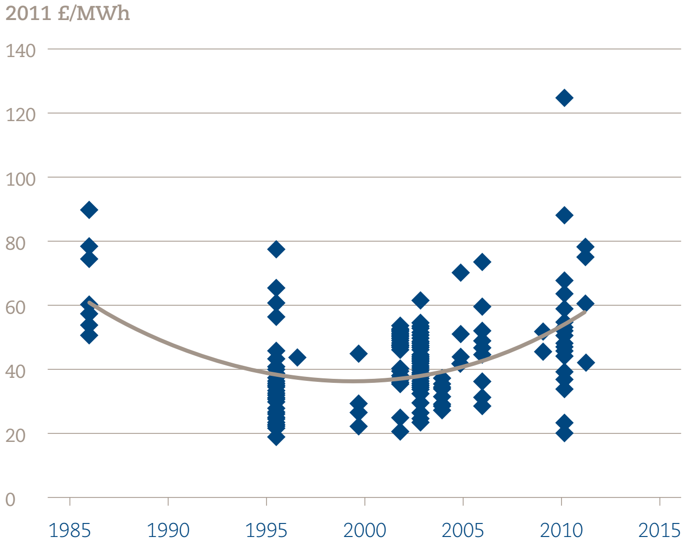
Nevertheless, the potential still exists for endogenous cost reduction in CCGT plant. This is partly because of savings arising from construction modularity and also due to the relatively short lead times for new plant, which can lower finance costs by limiting the period of financial risk and uncertainty (Castillo Castillo 2012). Indeed, reduced project lifetimes may also help CCGT cost forecasters by mitigating some of the inevitable uncertainties associated with the passage of time – at least for shorter term projections if not the more distant ones.

Cost out-turns

Turning to cost out-turns, the case study notes that because of the lack of commercial data from contractors, it is often unclear how contractual terms, technical assumptions and ancillary or administrative costs have been incorporated. For this reason reported 'actual' costs should broadly be considered as estimates for the purposes of this report.

Data for worldwide cost out-turn estimates from the late 1980s until the early 2010s are presented in Figure 4.4.

Figure 4.4: Range of worldwide out-turn estimates of LCOE for CCGT



Source: (Castillo Castillo 2012)

A comparison of Figures 4.3 and 4.4 suggest that early forecasts of approximately £40/MWh for actual costs at the turn of the century were in fact too conservative and underestimated the potential for costs to reduce to as little as £20/MWh by that time. However, it is also clear that forecasters did not foresee the extent of fossil fuel price increases experienced in the mid-2000s. For example, pre-2005 forecasts of levelised costs in 2010 predicted a range between £20 and £40/MWh, but estimated cost out-turns in 2010 lay in a range between £20/MWh and approximately £80/MWh (excluding one outlier exceeding £120/MWh)[14].

Main cost drivers and themes emerging from CCGT case study

The CCGT case study found a variety of cost drivers operating at different phases of the evolution of CCGT. This sub-section focuses on developments during the last three decades or so.

During the 1980s the primary cost-increasing driver could be characterised as a lack of meaningful competition. This was compounded by on-going technological improvements that were seeking higher efficiencies but were also creating increasing complexity of plant (Cleason and Cornland 2002). In addition, more stringent environmental regulation (applicable to all fossil-fuelled technologies) was limiting the pace of cost reductions (Islas 1999). Meanwhile, the main cost-reducing driver counteracting these factors during this phase was the relatively low price of the gas itself (Alterman 2012).

[14]Carbon pricing and regulatory changes also put upwards pressure on costs.

The low gas price continued into the 1990s and combined with several other cost-reducing drivers. First, technological improvements lead to efficiency gains (Islas 1999). Second, electricity market privatisation and liberalisation led to greater participation of private companies resulting in aggressive pricing for large CCGT contracts due to global competition among the leading suppliers (Watson 1997). Finally, shorter construction times, combined with the ability to deliver more standardised and replicable components, also offered the potential for cost reductions (Watson 1997, Islas 1999, Winskel 2002).

Counteracting these cost-beneficial drivers were two cost-increasing factors. One was the technical problems requiring costly remedial action that resulted from too hasty delivery of incompletely tested CCGT plant (in order to secure the few contracts available in the market) (Watson 1997). The other driver was the increase in plant complexity and the use of more expensive, advanced materials. Horlock (2002) points out that as thermodynamic limits to efficiency gains are approached so are the limits to complexity, as virtually no one part of the system can be made more efficient without incurring efficiency penalties in another part.

In considering the literature's expectations regarding future CCGT costs and its analysis of actual out-turns, the case study identifies four factors in particular:

i) Confidentiality and the type of data available

ii) Influence of fuel costs

iii) Fuel-dependent deployment and deployment-dependent learning

iv) Policy and responses to macroeconomic and geo-political forces

i) Confidentiality and the type of data available: A significant feature of the CCGT sector is the scarcity of data on actual generation costs. The methodological consequence of this is that many forecasts are derived from experience curves based on price data rather than cost (Junginger *et al.* 2008). Such curves have become generally accepted by analysts due to lack of actual plant operator data (Neij 2008). The main significance of using price data is that due to differences in cost and price trajectories, experience curves that are used to study short or specific time periods, particularly in early developmental stages, result in inaccurately reported learning rates (Neij 2008). We return to this issue of cost versus price data in Chapter 5.

ii) Influence of fuel costs: As already noted, the cost of CCGT power generation is most influenced by fuel feedstock costs. In the early 2000s, the fuel cost accounted for nearly 60% of generation costs in the UK (Parsons Brinckerhoff 2004) and considerably more in some countries (IEA 2005, IEA 2007). Future forecasting is thus considerably impacted by the volatility and uncertainty surrounding future gas prices. Chapter 5 considers the uncertainty of input costs in further detail.

iii) Fuel-dependent deployment and deployment-dependent learning: Learning is in large part derived from deployment whilst cost reductions are in turn dependent not only on learning rates but also on rates of deployment. However, over past decades the deployment levels of CCGT have been subject to significant fluctuation. One example of this occurred with the introduction of regulatory restrictions on the use of natural gas for power generation on both sides of the Atlantic as a result of the oil crisis in 1973 (Winskel 2002). The effect of the restrictions was that CCGT plant construction virtually ground to a halt; in the US, for instance, only one utility CCGT plant was built between 1979 and 1986 (Smock 1989). In fact, due to flexibility in the application of the gas turbine – extraction equipment and jet engines, for example – the technology has been able to survive periods of low demand in order to be deployed again later in CCGT plants (Watson 1997). Nevertheless, this example is a reminder of the challenges involved in forecasting future costs as a consequence of uncertain assumptions regarding future deployment.

iv) Policy and responses to macroeconomic and geo-political forces: In addition to technical development, learning and cost reductions (often derived from increasing deployment as noted above) have tended to be strongly influenced by energy and industrial policy as well as by general market dynamics. However, the different directions taken by evolving government policies have made cost reductions increasingly difficult to forecast. The case study identifies several key influences (Castillo Castillo 2012).

First, the development of gas turbines was, from its early stages, the subject of intense government support of military applications; in the US alone, military spending to improve the turbojet amounted to $450 million per year between 1976 and 1986 (Williams and Larson 1988). Second, cross-sectoral applicability has been a crucial non-policy market factor. Gas turbine use in military and civil aeronautics, surface transport, the chemical industry, blast furnaces and transportation of oil and gas has been a vital feature of the continued development of the core technology (Islas 1999). As already noted, this helped technology advancement to be sustained even if some of the main providers of the technology did not survive (Watson 1997). Third, CCGT deployment has been broadly favoured by the political responses to three societal concerns originating in the 1970s: security of energy supply; local safety and international security (especially regarding nuclear waste, reactor safety, and proliferation risk); and avoidance of environmental damage (Islas 1999). Finally, the liberalisation of national electric markets since the 1990s enhanced the operating flexibility of

CCGT plant. In particular, price linkages between gas and electricity markets may offer the owners of gas plant value which is not captured by traditional cost assessment methods, as we discuss in Chapter 2. This, together with the relatively low capital costs of CCGT plants (making the technology attractive where the cost of capital is high and/or the market outlook is uncertain), also contributed to a preference for investment in CCGT plants in many electricity markets (Roques 2007).

The CCGT case study comes to several overall conclusions regarding CCGT costs and cost forecasting. It is apparent, particularly over the last four decades, that exogenous factors outside the direct control of the industry (especially natural gas prices) have overshadowed learning effects with actual cost out-turns tending to be higher than forecasted. As the CCGT case study emphasises, forecasts made further into the future for technologies that are highly exposed to exogenous factors are especially vulnerable to being proved wrong.

In recent decades, regulatory change and fuel cost volatility have had the most influence on cost, deployment levels, and comparative attractiveness of generating technology. Future forecasts will need to address these more robustly and also clearly recognise that CCGT technology is now mature and that efficiency levels are close to thermodynamic limits. Future possibilities of noteworthy design changes are linked to the transfer of the combined-cycle to the upcoming deployment of integrated (coal) gasification combined cycle (IGCC) (Timera Energy 2011). In addition, manufacturers are focusing on flexibility of operation, in response to increasing penetration of intermittent renewables (Siemens 2011).

4.4 Carbon capture and storage (CCS)

Introduction

The case study (Jones 2012a) that supports this sub-section on CCS drew upon approximately 50 academic articles and grey literature reports. These were used for both numerical data and thematic analysis purposes. In line with the other case studies, the focus was on levelised and capital costs as opposed to CO_2 avoidance costs. However, the discourse on CCS also focuses on costs per unit of carbon abated, which has significant implications for the relative attractiveness of coal CCS and gas CCS.

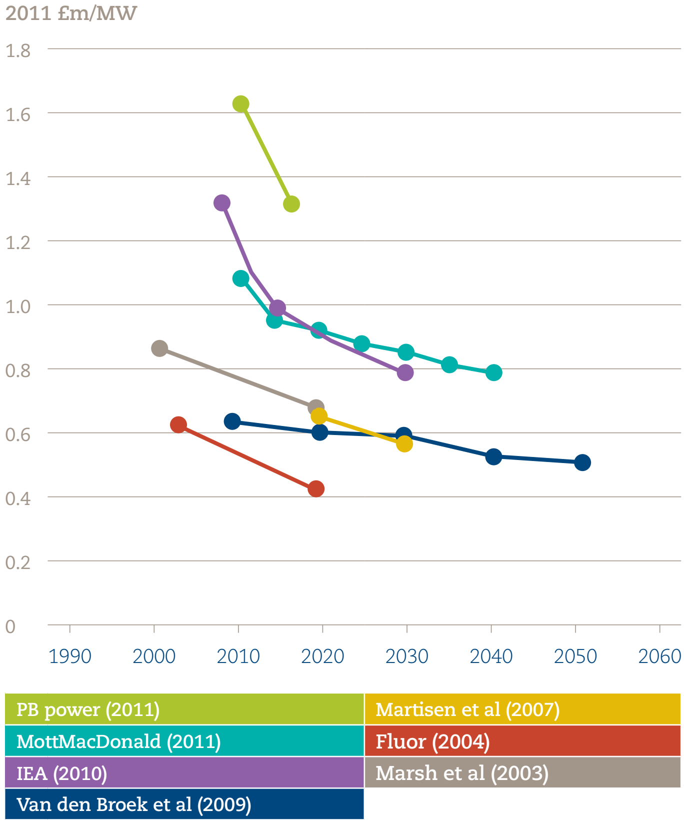
This sub-section differs from the other five in that there are no actual costs out-turn data for electricity generation with CCS because as yet there are no commercially operating plants (Global CCS Institute 2013). For this reason, all the data are by definition estimates.

Cost forecasts

Figure 4.5 presents seven forecasts of future gas CCS costs trajectories[15]. These projections are based primarily on experience curve analysis using assumed learning rates and rates of deployment, some based on the historical experience of flue gas desulphurisation (FGD). Some of the generic challenges of using 'analogue' technologies for experience curve analysis are identified in Chapter 3, and discussed further in Chapter 5. We consider their relevance to CCS in a later part of this sub-section addressing cost drivers and themes.

Although different pieces of evidence project differing rates of cost reduction, the literature mostly suggests that the rate of learning will be relatively steady. The consensus, as indicated by the graph below, has been for gas CCS costs to decrease over time, and projections for other key CCS technologies (e.g. post-combustion and pre-combustion coal CCS) to demonstrate similar patterns (Jones 2012a). Nevertheless, Figure 4.5 also shows how, over the period from 2003 to 2011, the starting level for the projections has increased significantly from between £600,000/MW and £900,000/MW in 2003/2004 to between £1,100,000/MW and £1,600,000/MW in 2010/2011. This is a reflection of the substantial increase in evolving estimates of contemporary costs, an issue examined in further detail below (Martinsen *et al.* 2007, van den Broek *et al.* 2009).

Figure 4.5: Range of forecast estimates of future capital costs of post-combustion gas CCS



Source: (Jones 2012a)

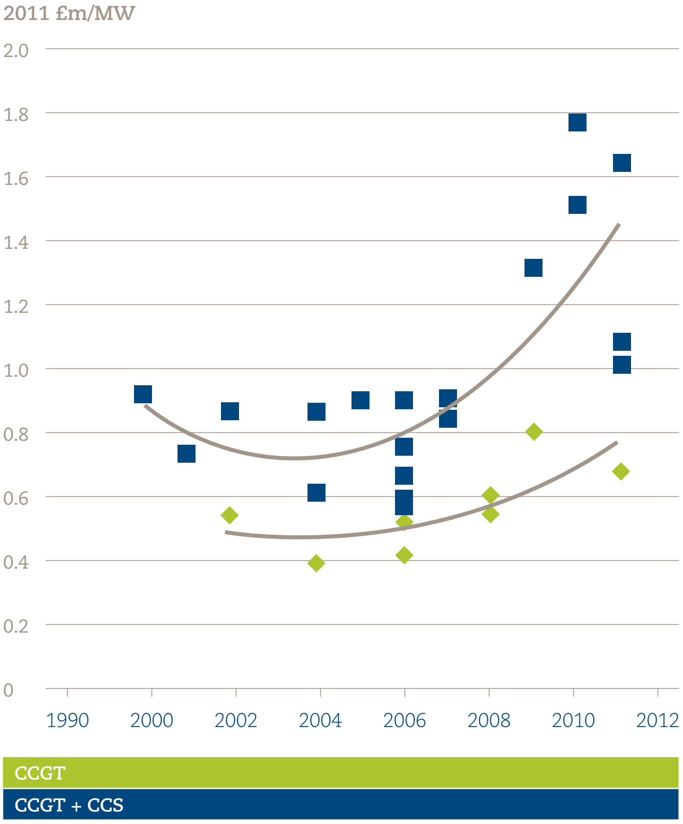
[15]The forecasts from 2011 are explicitly for future commercial projects (i.e. not demonstration plants), as is the forecast from 2003. The remaining forecasts are either a mix of projected costs for demonstration plants initially, followed by commercial deployment, or the distinction is not explicitly made.

Contemporary cost estimates

This section focuses on estimates of contemporary CCS costs at the time that the evidence reported it (as opposed to estimated forecasts of CCS costs at some point in the future). Here, the literature examined in Jones (2012a) has used both experience curve analysis and several variants of technological and engineering assessment including Front-End Engineering and Design (FEED) studies and expert elicitation.

Figure 4.6 below shows estimated contemporary capital costs of both unabated gas plant and CCS-abated gas plant. Comparing Figures 4.5 and 4.6, it is clear that early forecasts from 2003 and 2004, for example for gas CCS capex in 2011, were excessively optimistic. Marsh *et al.* (2003) and Fluor (2004) projected capex of approximately £750,000/MW and £500,000/MW, respectively, in 2011, whereas the contemporary 2011 estimates in Figure 4.6 lie in a range between approximately £950,000/MW and £1,650,000/MW (Jones 2012a).

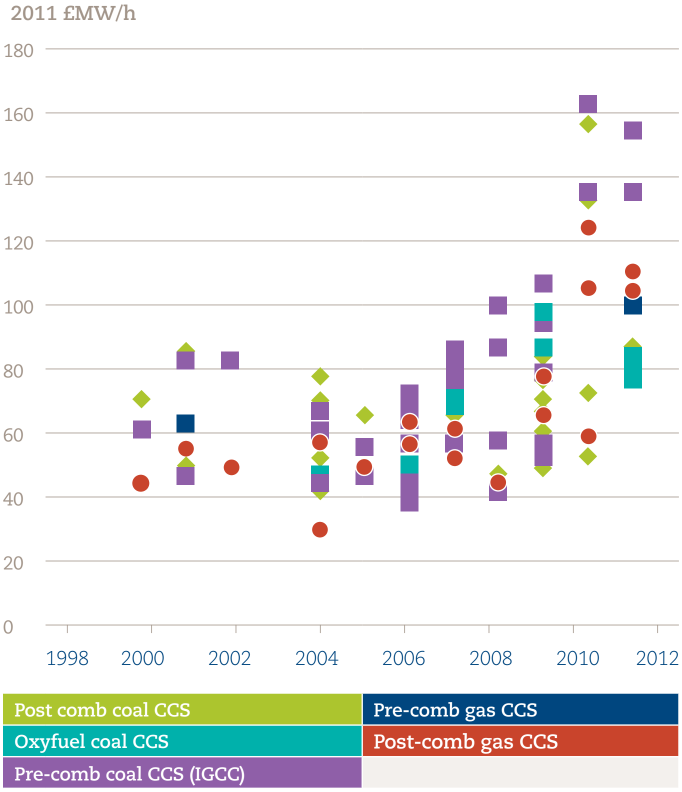
Figure 4.6: Range of estimated capital costs for gas plant, both unabated and abated



Source: (Jones 2012a)

Figure 4.7 presents data between 2000 and 2011 for estimated contemporary levelised costs for different CCS technologies. The estimates include the cost of electricity generation as well as the cost of CCS CO_2 abatement. Whilst the graph shows a wide variation in estimates within each year, it is evident that from the mid-2000s the overall trend has been up. In large part, this is due to escalation in the costs of the different generating plant, however the CCS portion of costs has been trending upwards as well (Jones 2012a). The later estimates would be expected to build upon earlier estimates and reflect the improved understanding and characterisation of the costs of the CCS technology suites. The reasons behind the cost increases are explored in the following section together with emerging themes.

Figure 4.7: Range of contemporary levelised cost estimates of CCS since 2000



Source: (Jones 2012a)[16]

Main cost drivers and themes emerging from CCS case study

Expectations of future CCS cost reductions are based on several drivers including increased project size, technological innovation, process integration, reduced construction times, and the development of an efficient carbon transport and storage network (Al-Juaied and Whitmore 2009, IEA 2010a, Parsons Brinckerhoff 2011).

However, the potential for reductions may be limited by two key factors, both of which are also considered further in the next chapter. First, with the exception of IGCC, the generating plant technologies are already technically mature which limits the scope for further learning (Viebahn *et al.* 2007, Al-Juaied and Whitmore 2009). Second, like nuclear power, CCS has a hazardous waste to

[16] To maintain the clarity of Figure 4.7, trends lines have been omitted, but the upward trajectory of cost estimates from the mid-2000s onwards is clear.

dispose of and the nuclear experience over the last fifty years highlights the potential for costs to continue to go up not down, in particular due to regulatory and safety demands (Rai *et al.* 2010, Mott MacDonald 2011). Indeed, as we have seen in Figures 4.6 and 4.7, estimates of contemporary CCS costs have in any case been rising for several reasons which are explored below.

One of the primary drivers of escalating CCS cost estimates has been supply chain bottlenecks that have increased engineering, procurement, and construction (EPC) prices for both coal and gas power plant. Manufacturing capacity constraints have increased prices for plant components and caused delivery delays that have increased the cost of project finance (Chupka and Basheda 2007, Mott MacDonald 2010). More specifically, advanced supercritical coal plant has been especially vulnerable to supply chain bottlenecks and thus the effect on cost estimates for post-combustion coal CCS has been particularly pronounced. The theme of supply chain and market dynamics is discussed further in Chapter 5.

During the period from the early 2000s to 2008, a further important driver of rising cost estimates was the high cost of raw materials such as steel, cement and copper caused by strong global demand (Davison and Thambimuthu 2009). As with supply chain bottlenecks, this led to increases in the cost of generating plant, rather than specifically to the CCS portion. Since the global financial crisis post-2008, commodity prices have reduced but this has been counteracted by increases in operating costs due to rising fuel feedstock prices (DoE/NETL 2010, IEA 2010a). Again, Chapter 5 considers in more detail the significant impact of high input costs.

CCS costs are of course subject to particular uncertainty because the technology is yet to be deployed at commercial scale anywhere. An additional driver of increased CCS cost estimates is an apparent tendency for early-stage engineering assessments to exhibit appraisal optimism, particularly in the form of over-simplified system design and of risk under-estimation (Jones 2012a). Scrase and Watson (2009) suggest that appraisal optimism is motivated by either the natural enthusiasm of interested parties or by the incentive of securing public funding. In any case, once projects and their costs are later defined and budgeted in greater detail, cost estimates tend to be revised upwards. A case in point is the cost estimates for retrofitting CCS to one of the units at Longannet coal-fired power station where estimated overall capex increased by nearly 14% from initial cost assessments and allowances for risk and contingency costs increased by nearly 90% (ScottishPower CCS Consortium 2011). Other reports also note that upward revisions to the magnitude of risk premiums have been a driver of increased cost estimates (EPRI 2007, Osmundsen and Emhjellen 2010). Chapter 5 explores appraisal optimism and realism in more detail.

In addition to the escalation in CCS cost estimates over the last decade or so, one of the main findings of the CCS case study is the extent of variation in the estimates, a theme we also return to in Chapter 5. In part, this is due to what the case study terms 'inherent variation' caused by specific project design and finance terms and also by project location. The choice of generating and capture technologies substantially affects a project's cost profile (Chen and Rubin 2009) and factors such as cost of capital and management ability are also significant (Mott MacDonald 2010, Simbeck and Beecy 2011). Locational differences are important too, in particular the options for CO_2 transportation and storage, and the availability or otherwise of cheap local fuel feedstock (WorleyParsons 2009).

The variation in CCS cost estimates is also due to imperfect knowledge and to unstandardised methodologies. The former is a cause of considerable uncertainty since it is not yet possible to verify estimates with empirical commercial-scale cost data (Shackley *et al.* 2009). Though many of the individual technology components are relatively mature, CCS as an integrated technology is still extremely immature resulting in substantial uncertainties over performance, economic life, and load factors (Chen and Rubin 2009, Giovanni and Richards 2010, Global CCS Institute 2011). In addition, future fuel prices are inevitably uncertain.

Unstandardised methodologies also contribute to variations in cost estimates. According to the Global CCS Institute (2011), the differing methodologies used for calculating CCS costs limits the comparability of different studies. For instance, many of the reports and papers reviewed for the CCS case study focused on CO_2 capture only and did not factor in transportation, storage and monitoring (Jones 2012a). Clearly, this can lead to misleading conclusions about the overall costs of CCS-abated power generation. For this reason, the IEA has called for the establishment of a common framework for CCS cost estimation methodology and terminology (IEA 2011).

In addition to the above concerns about estimation, further methodological issues relate to the forecasting of future CCS costs. The CCS case study emphasises the importance of recognising the limitations of the experience curve methodology. The technique of taking the learning rates of possibly analogous technologies such as flue gas desulphurisation and selective catalytic reduction and using them for CCS experience curves requires caution. Rai *et al.* (2010) emphasise the contingent nature of learning rates and argue that CCS cost reductions depend not only on technological development but also on deployment rates, the regulatory regime, and market structures. UK CCS CRTF (2013) also highlight how the approach taken to shared infrastructure development can bear upon costs. Rubin *et al.* (2007a) point out that there is precedent for power sector technologies during early commercialisation to experience cost increases not decreases. This suggests that actual cost out-turns for CCS could go up before they reduce. We return to these issues in the next chapter.

Overall, several key findings are summarised by the CCS case study. First, there is a pressing need for a greater degree of commonality in the methodological approach to estimating costs to ensure, insofar as it is possible, that such estimates are comparable. Second, the application of experience curves requires caution. Third, more consideration of project risk and potential supply chain bottlenecks is needed. Fourth, distinguishing between those cost drivers affecting generating plant and those specifically affecting CCS technology is important. Finally, the case study emphasises the fact that currently CCS cost data are only estimates and not actual out-turns. As such, they are subject to significant uncertainties and this is likely to compound the inevitable uncertainties of forecasting future CCS costs.

4.5 Onshore wind

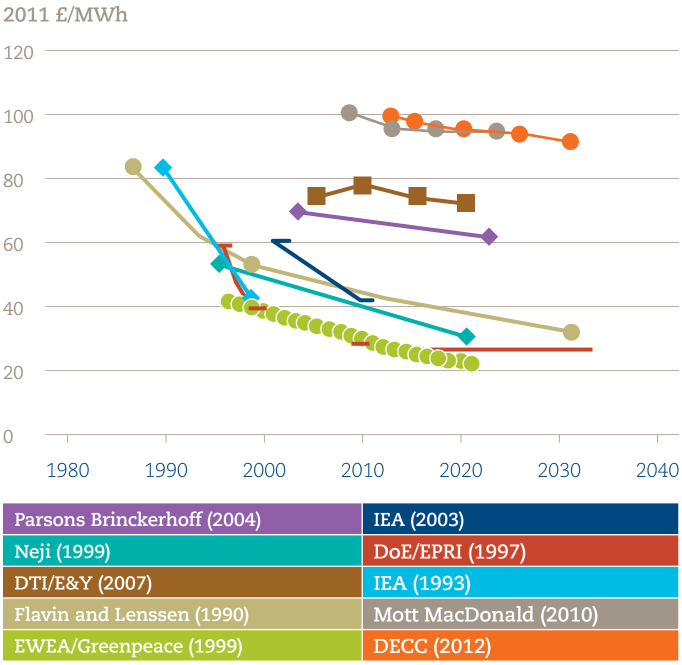
Introduction

The costs trajectory analysis for this onshore wind sub-section focuses on capex costs and on the levelised costs of energy (LCOE). The data for the onshore wind case study (Jones 2012b) was collected from more than 40 sources covering a range of countries. Given the short history of commercial wind technologies, data for pre-1990 forecasts is very limited, so the focus here is predominantly on the 1990s onwards.

Cost forecasts

Cost expectations for the onshore wind sector during the 1990s were for substantial reductions within a relatively short period of time. A study by Flavin and Lenssen (1990), for example, anticipated a reduction of levelised costs from over £80/MWh to under £50/MWh in a little over a decade. In 1993, the International Energy Agency (IEA) forecast cost reductions from a similar level down to £40/MWh by the year 2000 (IEA 1993). Figure 4.8 also shows how the starting point for levelised cost forecast trajectories reduced considerably during the 1990s, down to approximately £40/MWh by the end of the decade (EWEA *et al.* 1999).

Figure 4.8: Range of levelised cost expectations for onshore wind



Source: (Jones 2012b)

The methodologies underpinning these cost forecasts are varied, as are assumptions related to site specific factors such as wind speeds and load factors. The U.S. Department of Energy, for example, based its cost forecasts on technical and engineering assessment i.e. detailed projections of how onshore wind technology was expected to evolve (DoE and EPRI 1997). However, a more common forecasting approach, once the data was available, was to form future projections based on historic learning rates and experience curve extrapolation. For instance, the UK Government projected that onshore wind LCOE would fall to 75% of 1996 values by 2010 based on historic trends (DTI 2002b).

There is a considerable amount of attention to wind learning rates in the literature. For example, Neij (1999) suggested learning rates of between 4% and 7%, and EWEA *et al.* (1999) a learning rate of 15% until 2010, with the rate of cost reduction slowing after this period. Junginger *et al.* (2005) present a global learning rate of between 15% and 23%.

The early to mid-2000s saw an escalation in onshore wind costs. Because of this, as shown in Figure 4.8, the trajectory starting points increased to between £60 and £75/MWh. In addition, later forecasts tend to more explicitly acknowledge the uncertainty surrounding cost projections, and to address exogenous cost drivers such as commodity prices, whereas earlier forecasts often tended to focus more narrowly on technological development.

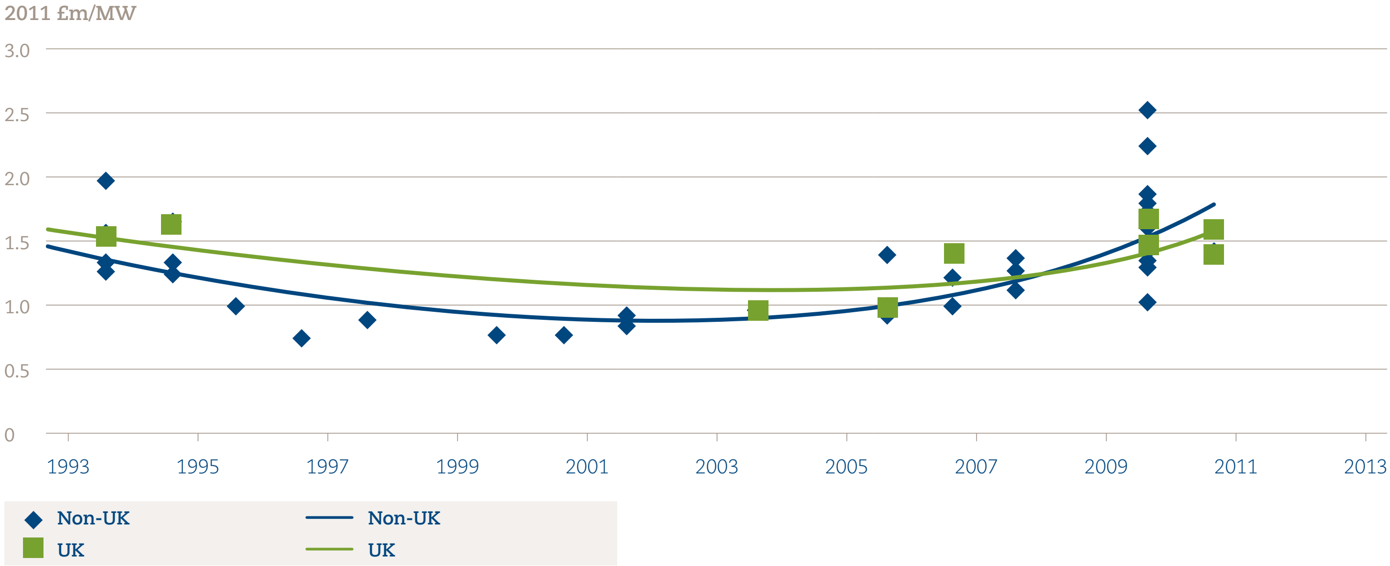
Recent cost projections anticipate modest cost reductions, again from a higher starting point. For instance, Milborrow (2011) suggests a 5-10% decrease by 2020, and a further, similar decrease by 2030. However, recent studies suggest that the potential for significant cost reductions from learning is likely to be limited, since onshore wind is now perceived to be a relatively mature technology (Mott MacDonald 2010, DECC 2012a). This is a theme that we return to in Chapter 5.

Cost out-turns

Turning to the reality of actual cost out-turns, Figure 4.9 below presents capital cost figures from 1994 to 2011. Installed capex tends to be broadly similar worldwide and UK project costs are comparable with project costs elsewhere in Europe (Milborrow 2012, GL Garrad Hassan 2010). Figure 4.9 shows how, on average and contrary to expectations, capex trended upwards from the early 2000s onwards. Junginger *et al.* (2005), for example, had suggested capex of substantially under £500,000/MW by 2010. In fact, actual capex out-turns in 2010 were in a wide range between approximately £1,000,000/MW and £2,500,000/MW.

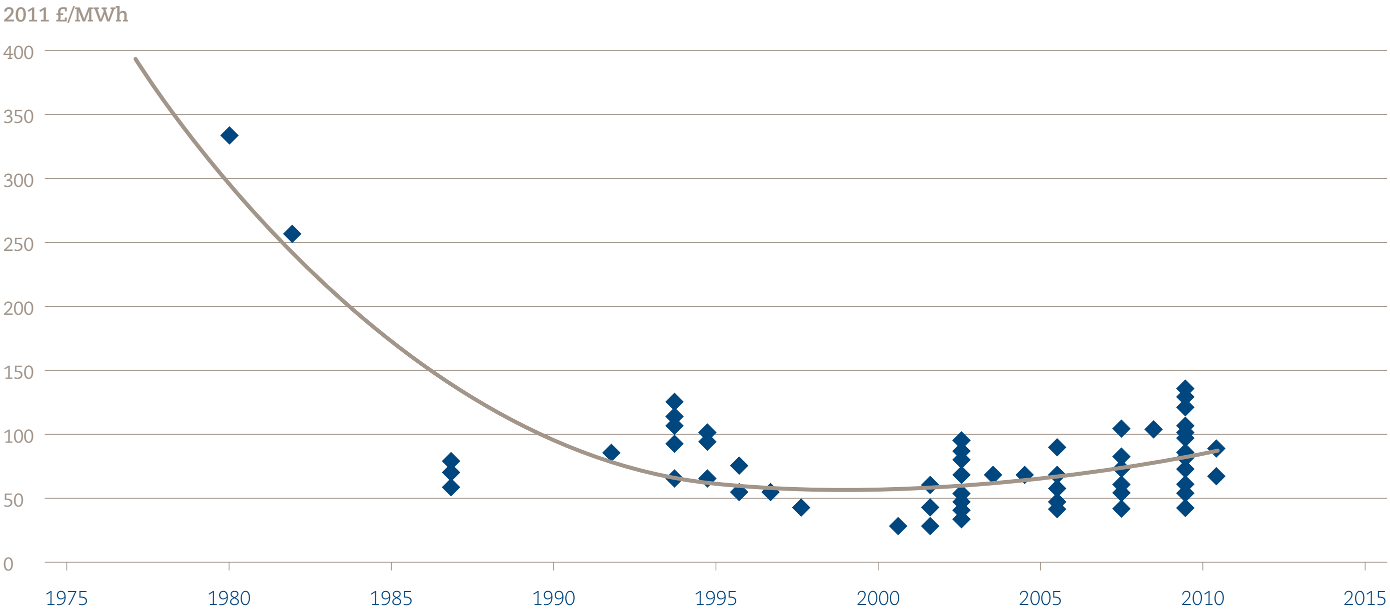
The levelised cost out-turns of onshore wind are presented in Figure 4.10. Note that the trend is less clear than for capital costs, because levelised costs vary significantly depending on the wind resource available (Blanco, 2009). There is also a potential trade-off between capex and levelised costs because optimising turbine designs to achieve reductions in overall levelised costs by improved load factors may drive up per MW capital costs. The cost of energy halved during the 1990s (EC 1999) and the graph shows that up until the early 2000s the expectations of cost reductions described above were broadly met, even if there was substantial variability in the actual amounts. However, from the early 2000s onwards, levelised costs began to escalate, diverging from earlier trajectory expectations. For example, according to five of the studies appearing in Figure 4.8 the costs of onshore wind energy in 2010 were expected to be between £30/MWh and £45/MWh. Figure 4.10 shows that 2010 levelised costs turned out to lie in wide range between £40/MWh and £135/MWh.

Figure 4.9: Range of capital costs of onshore wind 1994 – 2011



Source: (Jones 2012b)

Figure 4.10: Range of levelised costs of onshore wind since 1980



Source: (Jones 2012b)

Despite the setbacks of the early 2000s, projections made in the later 2000s that costs would continue to increase for several years and then reduce only insubstantially, have been proved incorrect. The average price of wind turbines declined by around 20% from late 2008 to 2010 (Bolinger and Wiser 2011), and fell further in 2011 (Milborrow 2012). Whilst detailed analysis would need to allow for factors such as operations and maintenance costs and site specific factors, both the above graphs showing actual out-turns suggest that a possible turning point may have now been reached with some signs of cost decreases occurring between 2010 and 2011.

Main cost drivers and themes emerging from Onshore Wind case study

Prior to the early/mid-2000s exogenous factors such as raw material costs were rarely cited in discussions regarding onshore wind cost drivers. Instead, the literature focused predominantly on several endogenous drivers arising from within the sector itself.

First, turbine upscaling resulted in significant cost reductions. In Denmark, for example, the average turbine size increased from 71 kW in 1985 to 523 kW in 1996 (EC 1999). Numerous economies of scale exist in turbine and tower manufacture and installation costs (driving down capex), and in operation and maintenance costs (driving down levelised costs) (Bellarmine and Urquhart 1996, EC 1999). Moreover, larger turbines mounted on taller towers tend to capture more wind which results in higher load factors and thus, again, lower LCOE (Lako 2002).

Second, wind forecasting and turbine siting improved significantly. For example, the European Wind Atlas Methodology was developed to map wind resources in the 1970s and 1980s. This has been cited as crucial to delivering productivity gains and reduced levelised costs because the correct location of each wind turbine is fundamental to the economics of a wind farm (Blanco 2009).

Technological learning and resulting improvements were a third driver of cost reductions during the 1980s and 1990s. Turbine rotor efficiency increased from 35-40% in the early 1980s to 48% in the mid-1990s (Neij 1999). Drive-trains were optimised, and improved understanding of how loads affect turbines led to lower usage of material (BTM Consult 2001). As capacity installed per year increased so the potential for economies of scale at the factory level increased (Bellarmine and Urquhart 1996). Economies of scale and learning effects are both themes that are explored in greater detail in Chapter 5.

From the mid-2000s, exogenous factors outside the influence of the industry either combined with, or overwhelmed, endogenous cost drivers with the result that capital and levelised costs went up again. Rising commodity prices contributed to the increase because wind turbines are relatively material-intensive (EWEA 2009). Steel, copper, and cement are all key materials in wind turbine manufacturing, and although the prices of these commodities fell back towards the end of 2008, there is a time lag before this can feed through to capex costs (Wiser and Bolinger 2009).

Another important driver has been sterling-euro currency movements (Arup 2011). From the UK's perspective, the weakening of sterling against the euro since mid-2008 significantly elevated prices for UK projects, which have typically been dominated by European imports (GL Garrad Hassan 2010). An additional smaller exogenous driver of cost escalation has been energy prices due to the effect on the costs of manufacturing and transporting turbines (Bolinger and Wiser 2011). Being beyond the immediate domain of the wind industry, these exogenous factors were difficult to predict and tended not to be factored into the cost forecasts for this period. Chapter 5 analyses a range of such exogenous themes in greater detail.

Whilst technological learning and upscaling continued to exert downward pressure on costs, these factors were overwhelmed by both the exogenous factors discussed above together with an additional endogenous driver – supply chain constraint. This played an important role in increasing capital costs, particularly during 2007 and 2008, although the congestion premium has since reduced (Mott MacDonald 2010, Mott MacDonald 2011). Shortages were experienced for a range of components such as gearboxes, bearings, generators, hubs and main shafts (de Vries 2008, Blanco 2009), and bottlenecks were compounded by difficulties in obtaining construction equipment (de Vries 2008, EWEA 2009). A key cause of such bottlenecks was the boom in demand for wind turbines in Europe and Asia, and particularly in North America due to the US Production Tax Credit (Blanco 2009, EWEA 2009, GL Garrad Hassan 2010). It is also important to note that (as in any industry) the extent to which turbine prices are fully reflective of underlying costs is a function of market dynamics and corporate strategy, particularly in the short-term. We return to the themes of market dynamics and policy effects in the following chapter.

An important conclusion is that the relative accuracy of the forecasts for the period prior to the early 2000s was, in large measure, due to the central role of endogenous drivers in determining early onshore wind costs. By contrast, more recent years have seen both exogenous factors and supply chain and policy effects play a much bigger part in influencing cost trajectories. Both engineering assessment and experience curve analysis have a much more limited ability to accurately anticipate and account for these drivers.

Due to the failure to adequately anticipate the cost challenges of the last decade, revised approaches to estimating onshore wind costs are now evident in the literature. There appears to be a greater recognition of the uncertainties and contingencies of cost forecasts, and scenario analysis is being used to help anticipate the impacts of differing macroeconomic and exogenous possibilities. In other words, there is greater appreciation that wind costs are not just driven by technical improvements but also by global forces such as currency movements, commodity prices, and market dynamics. This 'appraisal realism' is another theme that we examine further in the Chapter 5.

4.6 Offshore wind

Introduction

The offshore wind case study draws heavily on the data and analyses of UKERC's 2010 report on the costs of offshore wind in UK waters (Greenacre *et al.* 2010). UKERC reviewed approximately 350 pieces of evidence of which over 100 pieces were subsequently used in the report for data and analysis purposes.

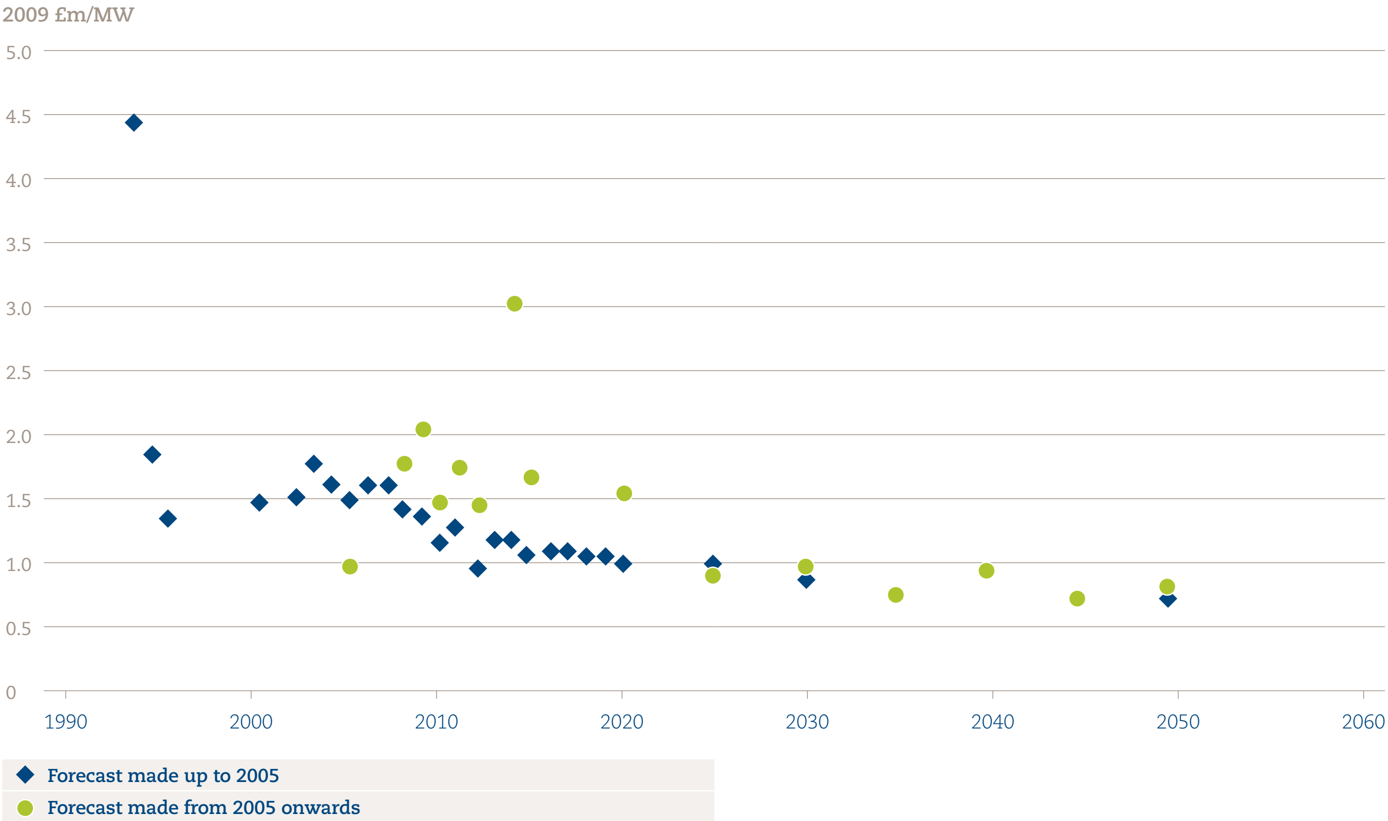
Cost forecasts

Early estimates of offshore wind cost trends were derived from engineering assessment, from what little cost out-turns data were available in the infancy of offshore wind development, and also from experience curves adapted from the onshore experience (Greenacre 2012b). As a consequence, the literature from the late 1990s onwards reflected a widespread expectation that costs would fall as deployment expanded and the industry matured. The grounds for optimism appeared justifiable and informed UK government thinking in the early 2000s (Greenacre *et al.* 2010).

The general expectation that costs would reduce over time is demonstrated by Figure 4.11 which presents a summary of the capex value forecasts between 1990 and 2050, as reported in the literature. The relationship between capital and levelised costs is complex, affected by factors such as reliability, efficiency and site optimisation. Nevertheless, the data reported in Fig 4.11 shows how expectations of capital costs have changed; it shows the in-year average forecast costs for two groups, one consisting of those forecasts made up to 2005, and the other consisting of those forecasts made from 2005 onwards. The year 2005 was chosen because the mid-2000s appears to have been a pivotal time when estimates of contemporary costs began to rise significantly from the lows of the early 2000s.

Whilst analysts consistently expected costs to fall over time, after 2005 forecast costs in the relatively near future rose as it became clear that capex had not fallen as originally anticipated. However, costs were still expected to fall in the longer term, returning to broadly the same level as earlier forecasts.

Figure 4.11: In-years means of offshore wind forecast capex, comparing pre and post 2005 estimates



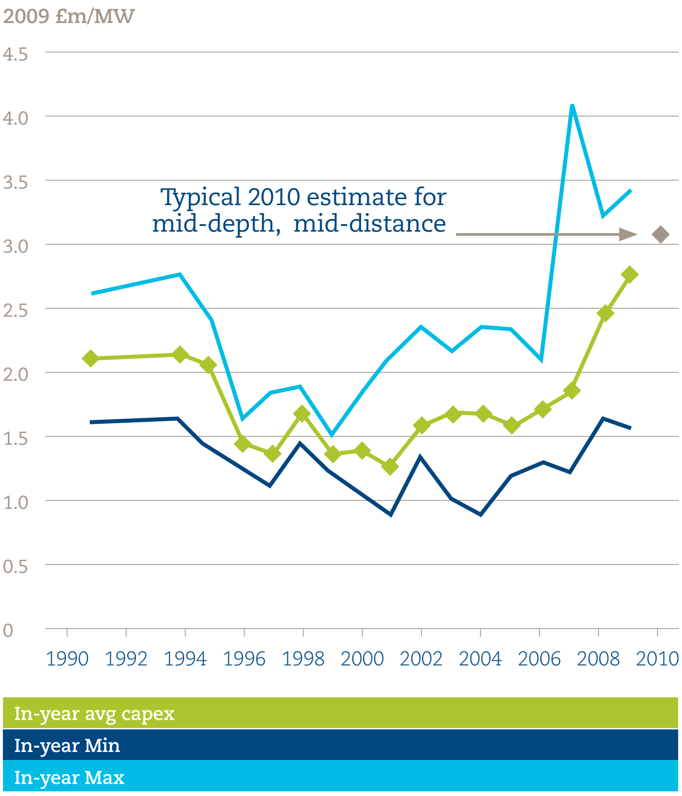
Source: (Greenacre *et al.* 2010)

Cost out-turns

Figure 4.12 shows what actually happened to offshore wind capex over the two decades from 1990. By the second half of the 1990s, and continuing through the early 2000s, offshore wind capex had fallen to approximately £1.5 million/MW. This was broadly in keeping with the small amount of forecast data shown in Figure 4.11 that is relevant to this period. However from the mid-2000s costs escalated sharply. Typical capex doubled from approximately £1.5 million/MW in 2005 to £3.0 million/MW in 2009. Given that past expectations of future capital costs in 2009 were approximately £1.25 million/MW to £2.0 million/MW, actual costs at that time exceeded previous expectations by between approximately 50% and 140%.

Meanwhile, the estimated levelised cost of offshore wind generation in the UK rose from around £85/MWh in the mid-2000s to up to £150/MWh by 2010 (DTI 2006, Mott MacDonald 2010). More recently, Mott MacDonald in 2011 estimated even higher energy generation costs at £169/MWh though the capital costs remained similar at around £3.0 million/MW (in a range between £2.8 million and £3.4 million/MW) (Mott MacDonald 2011). Similarly, the Arup (2011) report for DECC puts levelised costs at £174/MWh (large scale, medium scenario) though suggesting lower capital costs of approximately £2.75 million/MW. These estimates need to be seen in the light of the recently published draft strike price for offshore wind of £155/MWh for 2014/15 (DECC 2013c), and industry ambitions to drive costs down to level substantially below this figure over the next decade (The Crown Estate 2012).

Figure 4.12: Range of offshore wind actual capex, 1990 to 2009



Source: (Heptonstall *et al.* 2012)

Main cost drivers and themes emerging from Offshore Wind case study

There are a number of factors that lie behind the marked discrepancy between early expectations of future costs from the mid-2000s onwards versus actual cost out-turns in the latter half of the decade. Before considering the drivers of cost escalation we first address some methodological issues that are also relevant to the discrepancy.

At least until the mid-2000s, there was little primary data from which to construct experience curves. Offshore wind was still in its infancy with only 13 offshore wind farms constructed worldwide between 1991 and 2004 totalling less than 550MW of installed capacity. Before the year 2000, the UK had no offshore wind capacity at all and four years on there were only three completed wind farms totalling just 124 MW of installed capacity. Consequently, early forecasters borrowed and adapted learning rates and experience curves from the historically more mature onshore wind experience (Greenacre *et al.* 2010).

However the cost components, and the availability and resulting load factors of onshore and offshore generation are different and a comparison of the two is not like for like. Moreover, the literature exhibits a wide variation in learning rates for onshore wind and consequently many different experience curves for onshore wind power have been presented over the years e.g. Junginger *et al.* (2005), Neij (2008). Thus, whilst the borrowing of data from the onshore wind experience was an understandable response to the relative infancy of offshore wind development, the evidence suggests that experience curves were applied inappropriately and led to over-optimistic cost forecasting (Greenacre *et al.* 2010). In addition, whilst the literature revealed relatively few engineering assessments of future costs, again excessive optimism was also in evidence (Greenacre 2012b). Chapter 5 examines the themes of technological and deployment immaturity and of appraisal optimism in further detail.

Turning to the cost drivers themselves, the forecasts of on-going cost reductions in the offshore wind sector were based on expectations of continued benefits from learning, unit upsizing, economies of scale, and mass deployment (all these are themes we return to in Chapter 5). The reality, however, was that in the mid-2000s these drivers of cost reduction were overwhelmed by a number of opposing endogenous and exogenous drivers which caused upward pressure on costs.

Significant endogenous factors include an increase in turbine prices together with a supply squeeze in other components. Along with commodity price rises (addressed later), the rise in turbine prices was due in part to the cost of engineering/marinisation improvements in the face of poor generation availability experience (Greenacre *et al.* 2010). In addition, notes Gordon (2006), by the mid-2000s rapid growth in the US onshore wind industry caused by the US Production Tax Credit (PTC) scheme was resulting in a global shortage of turbine components, delaying European offshore projects and forcing up prices.

By 2007, turbine supply was the dominant bottleneck with the UK offshore sector squeezed by onshore turbine demand from China, India, and elsewhere in Europe as well as the US. BVG Associates (2007) and Douglas-Westwood (2008) reported that the combination of a strong market and constrained supply drove onshore turbine prices upwards by 30% between 2006 and 2008. Both national and extra-national policy effects are considered further in the following chapter, as are the themes of general market dynamics and competition.

Another potentially significant factor has been the lack of competition given the limited number of companies engaged in turbine manufacturing for the UK offshore wind industry (BWEA 2008, Carbon Trust 2008, Ernst & Young 2009, RAB 2009). The market has been dominated by Siemens and Vestas who together accounted for almost all of offshore turbines installed in the UK up to 2009 (Ernst & Young 2009), and may have been in a position to pass on high commodity and component costs to developers with relative ease[17]. In addition, the potential level of profit margin built into the price of turbines could have been obscuring the 'true' capital costs of offshore wind. The theme of price versus cost is also examined further in Chapter 5.

The offshore wind case study identifies two further endogenous cost drivers as being relevant. The first is the effect on costs of increasing depth and distance from shore in UK-specific offshore wind development. Collectively, and taking the average maximum depths and distances, UK Round 2 projects are nearly double the depth and more than double the distance of Round 1 projects (4C Offshore Limited 2010, Greenacre 2012b). Such increases can have a significant impact on construction, installation, electrical infrastructure, and O&M costs. Depth is of course a primary factor in engineering design and foundation size during the construction and installation phase. Of particular relevance to UK Rounds 2.5 and 3, The Carbon Trust found that foundation costs for sites in 40 to 60m of water were 160% greater than for sites in 0 to 20m of water (Carbon Trust 2008). Distance is a factor at the installation stage and also impacts on electrical infrastructure costs, in particular the amount of transmission cabling required (Ernst & Young 2009). Distance also increases O&M costs which in any case were impacted by inadequate marinisation of onshore-designed turbines (ODE Limited 2007). However, it would appear that the effects of increasing depth and distance may have been under-estimated in early cost forecasts (Greenacre 2012b).

In addition, a consequence of the above considerations was one further endogenous cost driver – poor reliability and availability leading to disappointing load factors. The load factor of a wind farm is determined by two variables: wind conditions and the availability of turbines and related equipment. In theory, a major advantage offered by offshore wind is that wind speeds are generally higher and more stable than onshore sites. Indeed, Snyder and Kaiser (2009) suggest that moving onshore to offshore should lead to an increase in the load factor from roughly 25% to 40%. However, UK offshore farms have experienced higher than expected loss of generation – in particular from gearbox failure, generator failures, subsea cable damage, and operator access limitations (BVG Associates 2007).

UK Round 1 projects experienced only 80.3% average availability[18] and as a result, the annual average load factor for reporting UK Round 1 wind farms has been 29.5% (Feng *et al.* 2010) – which is higher than the average value of 27.3% reported in 2007 for UK onshore wind farms but lower than the expected 35.0% for UK offshore and the reported capacity factors of at least 40% for some Danish offshore wind farms (Wind Stats 2009b, Wind Stats 2009a).

Again, actual out-turns have disappointed compared to prior forecasts – in this case the poor availability record was perhaps not anticipated in the UK because early European offshore farms proved to be relatively reliable. For example, the average annual availability of Denmark's well-established near-shore installation at Middelgrunden has been over 93% (Larsen *et al.* 2005).

In addition to the endogenous drivers and themes discussed above, the case study highlights three significant exogenous drivers of cost escalation: commodity prices; exchange rates; and the cost of finance.

Commodity prices rose significantly from the early 2000s until 2008 when the effects of the global economic downturn began to be felt. In the offshore wind sector, the most significant commodities are copper and, in particular, steel which has typically accounted for around 12% of total project cost (BWEA and Garrad Hassan 2009). From 2002 to 2007 the steel index experienced growth of 47% CAGR (compound annual growth rate) although in 2008 it fell by 58% returning to the long-term historic trend (Ernst & Young 2009). The increase in steel prices from the early 2000s was thus a likely contributing factor to turbine costs rising from £0.9 million to £1.5 million/MW (67%) in five years (RAB 2009). Steel price rises played an even greater role in the escalating costs of foundations. Foundation structures are heavily reliant on steel and costs increased from around £250,000/MW to £700,000/MW (a 180% increase) over the five years to 2009 (Ernst & Young 2009).

The Euro/Sterling exchange rate also contributed to the rise in costs borne by UK offshore wind developers. Around 80% of the value of a typical UK offshore wind farm is imported and has either been priced in Euros or priced in a currency tied to the Euro (Greenacre *et al.* 2010). O&M costs were also affected by the strength of the Euro. In addition, vessels and support services have been largely sourced from continental Europe, hence installation costs also rose (Ernst & Young, 2009). Since 2000, when the exchange rate was approximately €1 = £0.60, the Euro gradually increased in value against the pound, reaching almost one-to-one parity in December 2008. Consequently, until at least 2009 UK developers experienced continued increases in component costs because of the Euro's gradual appreciation.

A third exogenous driver has been the increased cost of financial capital. In theory, if an offshore wind developer were to use project finance, then the increasing experience in construction and operation should gradually reduce the risk premium for offshore installations resulting in a decreasing cost of capital (Greenacre *et al.* 2010). However, utility developers, who have been responsible for the majority of capacity installed to date,

[17] It is worth noting however that several other manufacturers are now entering the market (Heptonstall *et al.* 2012).

[18] This is average percentage of time that turbines were available to generate electricity. Actual generation and load factor depends on wind speeds during the times when turbines are available to generate.

instead typically used balance sheet financing (Ernst & Young 2009). The consequence of this was an increase in funding costs because of the 2007/2008 crisis in the global credit markets when the resultant rise in spreads for utility bonds from mid-2007 onwards led to a higher cost of corporate debt (Ernst & Young 2009). In future it is possible that a combination of increasing technological maturity, policy changes such as the Contracts for Difference envisaged in the UK's Electricity Market Reform package and changes to project financing arrangements could reduce the costs of capital (The Crown Estate 2012, DECC 2013c).

In considering the cost factors explored above, some of them could not have been easily anticipated, if at all. Commodity price rises and the Euro/Sterling exchange rate are prime examples, as perhaps was the state of the turbine market from which offshore wind developers suffered both too much competition (for example, from competing onshore turbine demand in the US) and too little (only two offshore wind turbine manufacturers). Chapter 5 explores all of these themes in further detail.

Nevertheless, whilst hindsight is a privileged point of view, it is reasonable to suggest that some of the sources of error should have been better anticipated, more rigorously scrutinised, or more clearly factored into the forecasting analysis. The effect of harsh marine conditions and of increasing depth and distance might have been more thoroughly considered. In addition, the early application of experience curves using learning rates 'borrowed' from a related sector was arguably not questioned enough. Again, this is a theme that we return to in Chapter 5 given that it has implications for other technologies in the early stages of deployment such as novel PV technologies and, in particular, CCS where there is no costs track record as yet and so learning rates are sometimes being borrowed from associated technologies such as flue gas desulphurisation (see this report's allied case study on CCS).

4.7 Solar photovoltaics

Introduction

The PV case study (Candelise 2012) draws upon over 70 sources in total, of which approximately 40 provided cost data. The data analysis focuses on the capital costs and prices of PV modules and systems rather than on levelised costs since the latter vary considerably depending on system type and location specifics, especially climatic conditions and irradiation levels. For actual out-turns, the PV system data presented are actual capital costs and the module price data are actual prices. However, module costs data are estimated production costs drawn from the literature and from PV company estimates and forecasts.

Cost forecasts

Since the 1970s PV technology forecasts, based on both experience curves and engineering assessment, have anticipated decreases in costs. Nevertheless, both the magnitude of decrease and the timing vary within the literature, and expectations have not necessarily matched outcomes, often being either too optimistic or too pessimistic.

Table 4.1 below, adapted from Schaeffer *et al.* (2004), presents data from five studies conducted between 1978 and 1996 which forecast future PV module costs via both engineering assessment and experience curve projection. The table shows that by the year 2000 module costs were expected to be anywhere between approximately $4 per Watt peak (Wp) and under $1/Wp. The data are compared with actual out-turns occurring in the year of projection in the following sub-section, but note both the wide range of estimates and also the marked discrepancy in each study between the engineering assessment and experience curves projections.

Table 4.1: Engineering assessment and experience curve projections of future PV module production costs adapted from (Schaeffer et al. 2004)

Study	Year of study	Year of projection	Engineering assessment ($/Wp)	Experience curve ($/Wp)
JBL86-31 target	1978	1986	1.63	0.86
JBL86-31 Cz	1985	1988	2.17	6.35
JBL86-31 Dentretic	1985	1992	1.02	2.80
EPRI 1986	1986	2000	1.50	0.79
MUSIC FM 1996	1996	2000	1.00	4.07

Turning to more recent forecasts, a study made in 2007, using engineering assessment, expected module costs to be €1/Wp by 2013 whilst two longer range experience curve studies, published in 2005 and 2006 respectively, anticipated costs of US$1/Wp for crystalline silicon (c-Si) modules in 2023 and US$0.7/Wp for thin film modules in 2022 (Surek 2005, Trancik and Zweibel 2006, EU PV Technology Platform 2007).

Regarding the PV whole system cost (i.e. module plus balance of system (BOS) cost), the UK government has commissioned several studies in the last five years for UK only PV costs. For example, a 2008 study (Element Energy 2008) projected costs in 2012 of £3.34/Wp and £3.12/Wp for small and large PV systems respectively. Longer term, the 2008 study anticipated small size system costs of £2.17/Wp by 2020. However, only four years later, Parsons Brinckerhoff estimated significantly reduced costs of £1.05/Wp for the same year and system size (Parsons Brinckerhoff, 2012). The following sub-section considers actual out-turns to date compared to earlier forecasts.

Cost out-turns

Figure 4.13 below shows how average PV module prices have decreased significantly since the mid-70s from nearly $40/Wp to approximately $2.25/Wp in 2012 (Maycock 2011, Solarbuzz 2012).

Referring back to Table 4.1 above and the projections made, for example, for 1992 and 2000 it is evident that with one exception the forecasts proved to be optimistic given that average module prices were still around $4.5 to $5.0/Wp in 2003. Whilst it is acknowledged that the comparison here is between cost forecasts and price out-turns, nevertheless the discrepancy is generally too high to be simply attributed to mark-ups (Candelise 2012).

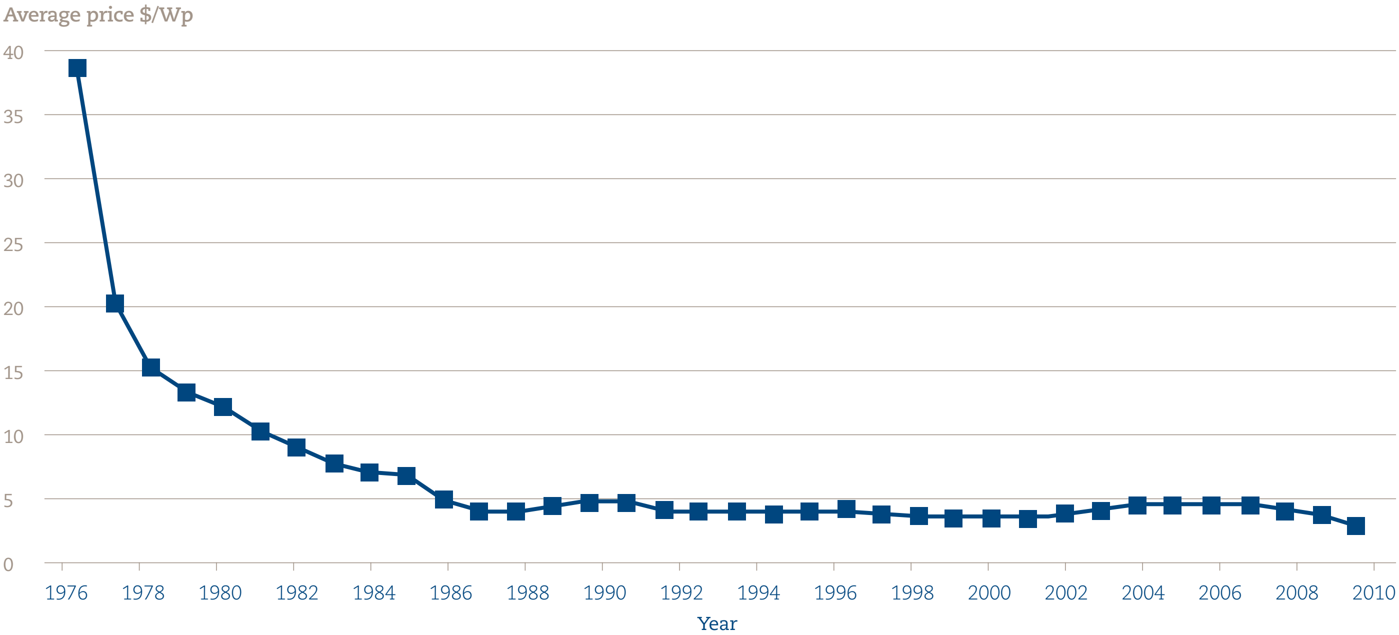
On the other hand, the 2007 engineering assessment referred to earlier anticipated module costs of €1/Wp by 2013 and this is proving to be a more accurate projection with several studies showing c-Si and thin film module costs currently approaching this figure or even bettering it (Ebinger 2011, Fath 2011, First Solar 2011, Holzapfel 2011, IHS iSuppli 2011, IMS Research 2012, Solarbuzz 2012). Meanwhile, the above-mentioned 2005 and 2006 studies that forecast out to the 2020s are now looking much too pessimistic, at least as far as timing is concerned. Similarly, the 2008 PV whole system price forecast for 2012 has also under-estimated the magnitude of recent reductions. Actual 2012 out-turns according to (Parsons Brinckerhoff 2012) for small and large system sizes in the UK were £2.54/Wp and £1.20/Wp respectively, being approximately 75% and 40% of the price out-turns projected just four years earlier.

In summary therefore, the history of future cost/price forecasting of PV modules and systems is generally characterised by over-estimation of future reductions in earlier years before 2000 and by under-estimation of reductions more recently. The following sub-section examines the predominant cost drivers and findings (described as 'themes') identified in the PV case study.

Main cost drivers and themes emerging from PV case study

The first major reduction in PV costs came in the 1970s when PV moved from space to terrestrial applications, with less stringent quality and reliability requirements and hence lowered costs. Since then, costs have continued to decrease (excepting the mid-2000s – see below), with learning rates typically in the 18-20% range.

Figure 4.13: PV module price historical trend



Source: (Maycock 2011, Solarbuzz 2012)

At the module level, the main cost reduction drivers have been innovation, learning and returns to adoption in either the module device itself or in the manufacturing processes. Commercial module efficiency and power density are still increasing whilst silicon usage in c-Si devices and other production costs have been significantly reduced over time, due to innovation and learning in cell design, improvements in silicon wafer cutting, and because of other production efficiencies such as automation, standardisation, and high throughput, high yield processes. In addition, c-Si technology has benefited from knowledge spillovers from the already mature semiconductor industry.

One particularly significant event has been the temporary shortage of silicon experienced during the mid-2000s when PV module prices rose in the short-term before falling dramatically in 2009 from approximately $5/Wp to under half that three years later. This silicon shortage was, in large part, caused by demand pull policies (primarily feed-in tariffs) implemented in key European countries such as Germany and Spain (Candelise 2012). The resultant increase in demand for PV modules caused silicon spot prices to go up from $50/kg to over $500/kg by 2008 (Flynn, 2009), increasing PV production costs and leading to an inversion in the historical trend of module price reduction. See also Chapter 5 where the effect of national policy on other countries is one of the themes examined in further detail. The consequence of the silicon bottleneck in the longer term, however, was increased innovation and efficiency together with more investment in silicon production and also a new wave of investment in thin film alternatives. Indeed, thin film PV modules are currently the cheapest to manufacture with one company producing at a cost of $0.74/Wp (First Solar 2011).

Of particular importance to cost reduction has been both the modular nature of PV technology which affords manufacturing efficiencies and has allowed a diversity of applications and easy implementation, and also economies of scale with the last decade seeing a huge increase in production capacity and average plant size. In 2007 average c-Si plant output size was around 100MWp/yr but this has now increased to at least the 500-1000MWp/yr range (JA Solar 2012) whilst CdTe module manufacturer, First Solar (which was the first PV manufacturer to reduce production costs below the $1/Wp production cost threshold) has increased its production capacity from 25MW in 2005 to over 2GW in 2011 (First Solar 2011).

Thus, scale economies, coupled with a dramatic expansion in the global PV market during recent years, have contributed greatly to the substantial drop in prices. In fact, evidence in 2012 suggests that modules may currently be selling at below production cost. This raises an uncertainty regarding the extent to which price reductions can be attributed to genuine cost reductions (e.g. from innovation and returns to adoption) or are the consequence of market dynamics (e.g. temporary pricing at lower than cost) and other factors such as easy access to cheap (subsidised) capital for Chinese manufacturers and competitive 'dumping' strategies (Candelise 2012). Indeed, data issues regarding the use of price in experience curves as a proxy for production costs is one of the emerging themes that will be explored in more detail in Chapter 5.

Another theme to emerge from the case study is the sensitivity of future forecasts to variations in system size, type, and location, and especially to variations in the learning and deployment rates used in constructing experience curves. Whilst the average PV learning rate appears to be around 20% even small changes can affect long-term estimates of cost reductions, the market expansion needed to reach a target cost, and the timing of such an achievement. For example, Trancik and Zweibel (2006) estimated that for a given learning rate thin film PV might cost $0.7/Wp in 2022, assuming a 30% capacity growth rate. In reality, the recent rapid capacity expansion means that $0.7/Wp is close to being achieved.

A related theme is that experience curve analysis is ill-suited to anticipating discontinuities in the learning rate as a result of radical technological break-through. This is especially relevant to a technology like PV where there exists the potential for radical innovation and step-change. A further consideration to the above is that so far experience curves have been tended to be based on historical data for conventional c-Si technologies, whilst very limited or no data exists for other emerging PV technologies, such as thin film or excitonic devices. Experience curves cannot be constructed for these technologies yet (except in a highly illustrative fashion) because of the absence of reliable data over a sufficiently long time period (Candelise 2012).

A theme that is shared by all the technologies reviewed in the case studies is the compound nature of the learning system. PV technology can be considered, at the very least, a two-part system consisting of the module and the BOS, each with its own cost drivers and learning rates. However, PV experience curves have mainly been developed for the module with relatively little quantitative evidence applied at the BOS level. This is in spite of the known differences in learning rates with some evidence indicating that inverters and installation labour costs exhibit learning rates of around 10% as opposed to the approximate 20% rate typically assumed for module costs (Schaeffer *et al.* 2004, IPCC 2011).

Finally, arguably the most important theme – again one shared by all the technologies reviewed – is the inevitable uncertainty and potential for error inherent in experience curve and engineering assessment forecasting. Referring again to the pre-2000 projections in Table 4.1, we have noted both the discrepancies between the two forecasting methodologies and also the over-optimism of both types of projection in comparison with actual out-turns once known.

Post-2000, neither experience curve nor engineering based studies were able to anticipate recent module cost/price reductions and consequently proved to be too pessimistic. Nevertheless, it is important to emphasise that forecasts have, for the most part, been consistently accurate about the general downward direction of the PV costs trajectory.

5. Themes, findings, and overall conclusions

5.1 Introduction

This chapter explores the principal drivers of cost increase or decrease, drawing upon the analysis in Chapters 3 and 4. These drivers vary considerably in character – some being quite technology-specific, others more policy-oriented or micro- or macro-economic in nature. They comprise a heterogeneous assortment of forces that impinge on costs trajectories and/or on the estimation and forecasting of costs, and we have chosen to refer to them as 'themes'.

Each of the themes has been identified in one or more of the case studies and in Chapter 3. Notwithstanding some inevitable overlap, each is categorised according to whether it is deemed to be 'methodological', 'endogenous' or 'exogenous' in nature. These terms are defined as follows:

- Methodological themes relate to issues arising from the collection, presentation, interpretation and comparison of cost data.
- Endogenous themes examine cost issues as they relate to learning effects and innovation, scale effects and standardisation, and technological, commercial and regulatory conditions within the sphere of influence of relevant actors, both governmental and industry.
- Exogenous themes address those cost issues that are largely beyond the ability of either the actors involved in a generating technology or policymakers more generally to influence, mitigate or in some cases predict. For example, general fluctuations in input costs - whether labour, components or raw commodities - due to macro-economic conditions such as a global economic downturn or boom, are considered to be largely outside the control of industry or an individual country's policies and are therefore treated as exogenous.

The following sub-sections consider each thematic category in turn. The final sub-section offers high-level conclusions including implications for costs forecasting.

5.2 Methodological themes

As noted, methodological themes relate to issues arising from the collection, presentation, interpretation and comparison of cost data. Several dominant themes of a methodological nature emerge from the case studies which support this report:

- Appraisal optimism
- Appraisal realism
- Technology and deployment immaturity
- Assumptions, system boundaries and extrapolations
- Price as a proxy for cost
- Compound learning systems
- Variability of estimates and forecasts

The above themes may broadly be characterised as describing issues either of accuracy in terms of forecasts versus actual outcomes, or of the variability and range of both forecasts and estimated outcomes at any given time. We first address issues of accuracy before concluding the methodological sub-section with a discussion of variability.

Appraisal optimism

It is evident from the case studies that cost forecasting has tended to exhibit periods of appraisal optimism where projections have under-estimated future cost outcomes. The literature suggests that in some cases this optimism has taken the form of a deliberate underestimation of costs in order to win policy support or to justify investments. It is argued that utilities may have had an interest in 'low-balling' costs as long as the estimates are non-binding, and that this has helped to get policy support (Cooper 2009). It has been suggested that in the 1960s power plant providers offered contracts with artificially low prices in order to penetrate markets. Only a few years later, cost estimates had risen by 80% (Kern 2011). Commentators on the nuclear industry have highlighted concerns about the strategic misuse of cost forecasts to garner policy support (Grubler 2010).

Similar observations have been offered with respect to the CCS sector, on the basis that attractive cost projections can help to secure public funding for demonstration projects (Scrase and Watson 2009). Strategic low bidding to secure NFFO contracts also occurred in the UK wind industry in the 1990s (Gross and Heptonstall 2010).

Alongside deliberate underestimation, natural optimism and stakeholder enthusiasm also play a role. Scrase and Watson (2009) note that early cost estimates of projects tend to be more optimistic than later estimates due to simplified system designs and to underestimating risks. Later, once projects are defined in greater detail and costs are more rigorously calculated, estimates tend to be revised upwards. This is illustrated, for example, by the costs study for retrofitting CCS at Longannet coal-fired power station where estimated capex increased by 13.6% from the initial Outline Solution (ScottishPower CCS Consortium 2011).

Meanwhile in the nuclear industry, Cooper (2009) notes that in the early 1970s, cost analysis was the domain of the utility industry, the reactor vendors and government officials. There were few financial markets analysts and independent energy consultancies expressing scepticism and higher cost estimates. Similarly, MacKerron (1992) argued that much of the nuclear data made public came from official nuclear agencies which tended to be positive about nuclear power. Certain assumptions, such as discount rates, could be too forgiving, and again the forecasts tended not to be informed by historical costs but to assume that 'past problems are always solved and new problems will not emerge' (Ibid.), i.e. substantial appraisal optimism anticipating significant cost savings compared to previous projects.

Appraisal realism

Despite the problems described above, some of the case studies did also demonstrate instances where earlier optimism and inaccuracy has been mitigated more recently by a greater recognition of the realities of cost forecasting.

As already noted, early cost estimates of CCS projects, for example, tend to be more optimistic than later estimates due to simplified system designs and underestimating risks. More recently, with projects being defined in greater detail, estimates have been revised upwards (Jones 2012a). Indeed, there has been a move to factoring in significantly higher contingency figures than was the case in the early 2000s, to reflect first-of-a-kind costs (EPRI 2007). For instance, a revised cost estimate of CCS retrofit of Kårstø gas-fired power station in Norway factors in substantially higher contingency reserves than the initial cost estimate; this is in recognition that CCS investments are 'mega-projects' with substantial risks of cost overruns (Osmundsen and Emhjellen 2010).

Similar considerations are noted with respect to nuclear. According to Parsons Brinckerhoff (2010), one reason that nuclear generation cost estimates in the UK rose 40% between 2008 and 2010 was because preparation for new nuclear plant construction resulted in a clearer picture of costs. Tendering for plant internationally meant that up-to-date cost data were more widely available thus enabling more realistic estimates.

The case study for onshore wind observes that, in the second half of the last decade, revised approaches to estimating costs become evident in the literature due to the failure of experience curves to adequately anticipate the cost challenges faced. A greater recognition of the uncertainties and contingencies of cost forecasts has become apparent, and scenario analysis is being used to help anticipate the impacts of differing macroeconomic, exogenous possibilities. In other words, there has been a greater appreciation that wind costs are not just driven by technical improvements but also affected by uncertain exogenous forces such as currency and commodity prices (Jones 2012b).

In contrast, forecasts were accurately realised during the 1980s to mid-2000s because experience curves can effectively predict endogenous change and analysis suggests that during this period the key cost drivers for onshore wind were indeed endogenous rather than exogenous (Jones 2012b).

Technology and deployment immaturity

The maturity of a generating technology and the extent of its deployment can be significant factors in the process of projecting future costs. For example, PV experience curves are based on historical data for conventional silicon technologies and limited (or no) market data exists for emerging PV technologies, such as thin film or excitonic devices. CCS technologies have no market experience at all (although various components of a CCS system do), and similar difficulties are associated with various marine technologies and other emerging options.

The PV case study also highlights the inability of experience curve analysis to anticipate discontinuities or step-changes in the learning rate. This may make experience curves inadequate for predicting cost trends in discontinuous technology fields such as PV where technological breakthroughs are expected to occur when novel technologies reach commercialisation (Candelise 2012).

The case studies illustrate the risks associated with 'borrowing' data from seemingly analogous instances. In the case of offshore wind, with little primary data from which to construct experience curves, early forecasters borrowed and adapted learning rates from the historically more mature onshore wind experience (Greenacre *et al.* 2010). However the cost components, and the availability and resulting load factors of onshore and offshore generation are different and a comparison of the two is not like for like. Moreover, the literature exhibits a wide variation in learning rates for onshore wind (Greenacre *et al.* 2010) and many different experience curves for onshore wind power have been presented over the years (e.g. Junginger et al. (2005); Neij (2008)). Various exogenous factors also overwhelmed any learning (see below). Thus, whilst the borrowing of data from the onshore wind experience was an understandable response to the relative infancy of offshore development in the early 2000s, the evidence suggests that experience curve based analyses did not provide an accurate projection of costs from the mid-2000s onwards.

This issue is of current relevance to CCS forecasting. Cost projections for post-combustion gas CCS are mostly based on experience curve analysis, including the application of historical experience curves for flue gas desulphurisation (FGD) and selective catalytic reduction (SCR) (Jones 2012a). This approach of applying the historical learning rates of apparently analogous technologies to CCS might initially be considered apt since they too are pollution abatement technologies operating in the power sector (Watson *et al.* 2012), although some commentators, for example Rai *et al.* (2010), highlight the contingent nature of learning rates. Until there is empirical utility-scale experience of CCS it is perhaps too early to confirm the robustness of theses analogies.

One response to the lack of market data for nascent technologies is that in the early stages technical and engineering assessment should perhaps be favoured over the use of experience curves. It should be noted however that techno-engineering assessment can also be liable to significant error. For example, nuclear cost projections have, from the outset, been derived mainly from engineering/ technical assessment rather than from experience curves (Greenacre 2012a). This has not prevented some substantial discrepancies between forecasts and outcomes. Similarly, in the offshore wind sector, whilst the literature reviewed reveals limited evidence of engineering assessment analysis, here too estimates of the future costs of offshore wind tended to prove optimistic compared to the reality (Greenacre *et al.* 2010). Meanwhile in the PV sector, engineering assessments have been over-optimistic in assessing future costs up to the early 2000s, and have then underestimated cost reductions in the last decade (Candelise 2012).

Assumptions, system boundaries and extrapolations

It is clear from the evidence that costs projections can differ considerably depending on a variety of omitted or included factors, and the differing assumptions about them. Many of these assumptions, such as judgements concerning discount rates and O&M costs, are relevant to each technology. Others are specific to only one or some of them.

Extrapolating historical trends is essential to forecast methodologies but also carries significant risks. Extrapolated experience curves, for example, are dependent on the assumed learning rates which in turn are defined by the historical period chosen for learning rate/progress ratio measurement. Likewise, such extrapolations, when time-based, are also dependent on assumptions regarding rates of deployment since learning rates by themselves simply describe a relationship between cost reduction and installed capacity. However, deployment rates can be highly uncertain (Rubin *et al.* 2007b).

The PV case study observes that the extent and timing of future cost reduction is very sensitive to the estimated learning rate, which in turn is also affected by the underlying data used (the period and scope covered). Even small changes in learning rate can affect long-term estimates of cost reductions, the market expansion needed to reach a given target cost, and the potential timing for such an achievement. Similarly, varying forecasts of future market growth affect the estimated timing for achieving a cost reduction target (Candelise 2012). For example, Trancik and Zweibel (2006) estimated that the cost of thin film PV could reduce to between $0.5/Wp and $0.7/Wp by the period 2016 to 2022 (assuming market growth rates that ranged from 30% to 70%). In reality, 0.7$/Wp is already very close to being achieved by thin film, i.e. much earlier than estimated due to high market growth rates (above 70% in 2010 (Mints 2011)).

System boundary choices can lead to confusion over the comparability of estimates. This is a particular issue for 'network' options such as CCS. The Global CCS Institute (2011) suggests that the differing methodologies used for calculating CCS costs limits the comparability of different studies. For instance, it is striking that many of the papers reviewed did not factor in costs for CO_2 transportation, storage and monitoring, instead focusing on CO_2 capture only. As Rubin *et al.* (2007b) highlight, this omission can lead to differing conclusions about the relative total cost of different CCS technologies.

However, system boundary issues also affect renewables; for example, whether grid extension and upgrading, and additional system balancing requirements are included. A wide range of other factors can be treated differently in different studies. These include whether costs are 'overnight' (see Chapter 2) or include interest during construction, choice of discount rate, load factor assumptions, and how O&M costs are accounted for.

Price as a proxy for cost

Another problem for market based analysis is that of cost data versus price data. Equipment suppliers and installers tend to guard their design, construction, and operations costs closely such that it can be problematic constructing a time series for actual manufacturing costs. As a result, market conditions can affect perceptions of cost over time, which may be misleading if for example the market allows suppliers to extract excess profits, or indeed if oversupply leads to equipment being sold below cost price.

For example in the PV sector, experience curves generally use module prices as a proxy for their production costs. However, module price movements have varied considerably as a result of demand/supply conditions (Candelise 2012). For instance, substantial demand and profit margins in the second half of the 2000s drove high levels of investment in the PV sector (Jager-Waldau 2006, Jager-Waldau 2008). However by 2010, production overcapacity led to a dramatic drop in global module prices.

A not dissimilar situation has also been evident in the offshore wind sector during the late 2000s where the turbine market was dominated by Siemens and Vestas. Together, these two suppliers accounted for 98% of offshore turbines installed in the UK up to 2009 (Ernst & Young 2009). They may thus have been in a position to pass on high commodity and component costs to developers with relative ease. Again, the potential profit built into the price of turbines could periodically obscure the 'true' capital and levelised costs of offshore wind.

Due to commercial confidentiality industry analysts have generally accepted the practice of using prices as appropriate (Neij 2008). The pitfalls of this practice have been elucidated amongst others by the analysis of the Boston Consulting Group (1972) which highlighted that differences may occur between cost and price development in various intervals but also that sustained price reduction can reflect a true cost reduction for already established products. In the case of CCGT, one of the most comprehensive reviews applied the experience curve methodology using price data, and concluded that part of the price trajectory reflected the pricing strategy of the main providers to gain access to markets (Cleason and Cornland 2002, Neij 2008).

Compound learning systems

As discussed in Chapter 3, there is debate in the literature about the disaggregation of learning from 'system' level into component parts. Typically, in the formulation of learning rates for experience curves, a generating technology is viewed as one system with a single learning rate. This is a useful simplification of a more complex reality – that each technology is a compound system possessing the potential to be broken down into multiple sub-systems operating under distinct conditions, each with their own learning rates and resultant experience curves. This applies to all the technologies but in what follows we use PV and CCS as cases in point.

PV experience curves have been mainly developed for PV module costs, yet PV should more accurately be addressed as a compound learning system, accounting also for learning trajectories and cost reductions at the BOS level, which refers to all other system components and cost.

The PV case study argues that learning rates based on historical module trends cannot be applied to PV system learning nor can system level cost reductions be attributed to the learning and cost reductions of individual system/hardware components. Rather, they are the result of the combined effect of several factors. In fact, there is relatively limited quantitative evidence on the drivers of cost reductions at BOS level, as most cost reductions efforts (and most research literature) have concentrated on the module (Candelise 2012). This situation reflects the following difficulties:

- BOS costs differ for different PV applications, e.g. grid-connected versus off-grid and also between different grid-connected applications such as roof mounted, ground mounted, building-integrated (BIPV);
- There are wide regional differences in system designs and in implementation and installation, which makes cross-country comparison difficult;
- PV system cost reductions are affected by distinct conditions such as country specific market developments, and policy and regulatory environments. Thus, learning rates experienced in one country cannot be simply transposed to another one with a different regulatory and market context.

For these reasons reliable input data over a sufficiently long time period are not readily available for BOS, thus limiting the use of experience curves as both descriptors of past trends and as a forecasting tool for system level costs (Candelise 2012).

Some additional issues emerge from the CCS study. Here, the learning system can at the very least be viewed as a binary one, involving the underlying coal or gas plant as well as the CCS technology itself. However, the generating plants to which CCS will be fitted (with the exception of IGCC) are already technically mature which limits the scope for further improvement (Viebahn *et al.* 2007, Al-Juaied and Whitmore 2009).

On the other hand, as already noted, the CCS technology as yet has no commercial track record on which to base future cost projections. Additionally, the case study observes that many of the exogenous and endogenous factors for CCS apply primarily to generating plant, whereas the methodological factors tend to apply to CCS technologies. It is important to make explicit this distinction between cost drivers affecting generating plant (which can be quantified with greater certainty) and drivers affecting CCS technology itself (which are less certain). The literature does not always make this distinction clear (Jones 2012a).

Variability of estimates and forecasts

In addition to the gaps between expectations of cost and subsequent reality, the case studies demonstrate that both projections and actual outcome data are in any case subject to substantial variability at any given time. This can be due to a variety of reasons which may be categorised as inherent variation, imperfect knowledge, and additional methodological issues.

Inherent variation refers to the drivers of cost variability arising from the specifics of a project, in particular the design of the generating technology and/or system employed, fuel price where applicable, contractual/financing arrangements, management performance, and the location of the project. All these bring distinct effects which, for any given year, can result in cost differences between seemingly similar projects, both projected and actual.

With CCS, for example, the choice of capture technology – post-combustion, pre-combustion or oxyfuel – significantly affects the cost profile of projects, as does the capture efficiency and project size (Chen and Rubin 2009). More broadly, the specific financing arrangements associated with the project are crucial. Factors such as the cost of capital and the ability of the project developer to manage outgoings are also significant (Mott MacDonald 2010, Simbeck and Beecy 2011).

Locational differences can also significantly affect CCS costs, as they can PV and wind costs. With CCS for example, geographical location substantially affects the transportation and storage options available – for instance, whether there is potential to reduce transport network costs through clustering with other CCS installations (Jones 2012a). The presence of a CO_2 transport infrastructure can also reduce risk and therefore cost of capital (UK CCS CRTF 2013).

Moreover, the cost and type of fuel also varies significantly depending on location; for instance, levelised cost estimates for gas CCS in Saudi Arabia are relatively low due to cheap local natural gas supplies (WorleyParsons 2009). Other locationally-differentiated drivers of costs variation are labour rates (WorleyParsons 2009); legal costs such as acquiring permits and licences; and national policies such as carbon taxes. The local characteristics of each particular market can also affect the cost of financing.

As previously mentioned, the variability in PV system prices can be due to differences in markets, system size and types, and countries. Prices tend to be higher in residential markets compared to medium size commercial systems and large utility-scale systems. They also differ across PV system types, with BIPV systems, for example, being more expensive than standard roof top applications (Candelise 2012).

Module prices also vary quite widely and the PV case study notes that a monthly survey of retail prices demonstrates significant variability according to the module technology, the module model and the manufacturer, its quality as well as the country in which the product is purchased. For example in March 2012 average retail module prices were respectively $2.29 /Wp in US and €2.17€/Wp in Europe, but the lowest retail price for a crystalline silicon solar module was $1.1/Wp (€0.81/Wp) and the lowest thin film module price was $0.84/Wp (€0.62/Wp) (Solarbuzz 2012).

In studying the methodological variability in forecasts for CCGT two aspects can be discerned. First, after the fuel shock prices in the 1970s, 1980s and 2000s, forecasters started assigning a higher priority to fuel cost variability from 2005 onwards (Castillo Castillo 2012). Second, forecasters have chosen different methods to cope with this variability, which range from probability density functions of fuel cost influencing factors, through to borrowing from forward-market price projections or even just expert opinion. This is evidenced by the strikingly higher variability in forecast costs amongst post-2005 forecasts relative to pre-2005 ones.

The nuclear case study also highlights several considerations regarding inherent variability in the cost data (Thomas 1988, Tolley and Jones 2004, MacKerron *et al.* 2006, Harris *et al.* 2012). These include:

- costs vary with reactor technologies and estimates for the same technology can also differ, depending for example on whether first-of-a-kind (FOAK) or nth-of-a-kind (NOAK) is assumed;

- capital costs and costs of generation are country, region and regulatory environment specific – there have been substantial differences of performance in different countries and in different utilities within the same country where regions face different input costs, especially labour;
- actual or assumed construction time is highly significant – delays affect both construction costs (especially labour) and, in particular, financing; and
- also important are productivity variance including operating experience and other factors affecting load factors (see for example Gross *et al.* (2007))

The other drivers of variation in cost projections and estimates appear to reflect not real-life differences, but rather imperfect knowledge and other methodological issues.

Imperfect knowledge applies inevitably to costs projections since forecasting the future carries intrinsic uncertainty. This is exacerbated currently in the case of CCS because it is not yet possible to verify estimates with empirical commercial-scale cost data (Jones 2012a). Although many of the technology components are mature, CCS as an integrated technology is itself immature, leading to high levels of uncertainty about performance (Giovanni and Richards 2010).

Imperfect knowledge can also apply to 'actual' cost outcomes. As we have seen, costs are not always transparent to outside observers and price is not necessarily a satisfactory proxy. For example, Harris *et al.* (2012) point out that reactor costs are difficult to estimate due to the variety of commercial terms associated with a vendor's quote and because of the lack of transparency behind the majority of published estimates. Indeed, as noted in Chapter 4 much of the data available in the literature are estimates from academic and governmental analysts and other industry observers – i.e. what are presented as cost outcomes are not genuinely 'actual' but are in fact estimated (Greenacre 2012a).

There are a number of additional methodological issues not already discussed in this sub-section which can also contribute to the variation in cost data expressed at any given time:

- inconsistency in cost estimates due to the presentation of the year to which an estimate applies – with some reports focusing on the commissioning date, others the date of first capital investment (Jones 2012a);
- unclear price base for estimates with different estimates sometimes denominated in prices of different years (MacKerron *et al.* 2006);
- use of sensitivity and scenario analysis which produces numerical ranges categorised, for example, as 'high', 'middle' and 'low' or 'worst case' versus 'best case' (applicable to some of the data for all of the case studies).

5.3 Endogenous themes

As noted, endogenous themes examine cost issues which lie within the sphere of influence of the sectoral actors, both governmental and private sector. The case studies reveal a diversity of endogenous themes with the potential to impact the capital and/or levelised cost trajectories of the generating technologies reviewed and which can therefore either support or adversely affect the accuracy of future costs forecasting. Often the themes have a variety of aspects or sub-themes, each of which is exemplified by one or more of the technologies. The endogenous themes can be categorised as follows:

- Learning effects
- Barriers to learning
- Economies of scale
- Standardisation
- Country and market environment
- Policy environment
- Regulatory environment
- Physical environment

Learning effects

As we explored in Chapter 3, costs are typically expected to go down over time, in large part due to increasing returns to adoption which include various types of learning effects, in particular learning-by-researching and learning-by-doing. Furthermore, those technologies considered being at less mature stages of development and deployment will generally be thought to have more substantial learning and cost reduction potential. Thus, unless learning occurs at least to the extent assumed in a forecast, projections about future costs are likely to prove inaccurate , irrespective of the other factors that also influence them.

The case studies provide a variety of examples of learning and consequent cost reduction. In the onshore wind sector, for instance, rotor efficiency of turbines increased from 35-40% in the early 1980s to 48% in the mid-1990s (Neij 1999). Drive-trains were optimised, and improved understanding of how loads affect turbines led to more accurate calculations of the physical limits of materials resulting in a lower weight (BTM Consult 2001).

Learning – through research, spillover, and manufacturing – has played a key role in the falling cost trajectories seen in the PV sector. For example, as a result of research at the device level, the c-Si technologies have seen significant increases in both cell efficiency and power density of the module and a reduction in silicon consumption per Wp. An increase in cell efficiency of 1% is able to reduce cell costs per Wp by 5-7%. In the last five years, commercial module efficiency has improved from 12-14% in 2007 to 13-16% in 2011 for average crystalline silicon modules, and from 15-17% to around 20% for the best performing modules (EU PV Technology Platform 2007, EU PV Technology Platform 2011, Green *et al*. 2012).

In addition, silicon usage in PV cells has been reduced thanks to innovation (in large part stimulated by the silicon shortage in the mid-2000s) that has allowed thinner wafers and improving efficiencies in wafer cutting (i.e. reducing wastage of material). A further significant factor is that, over the last decade, module production processes have become more automated, gradually moving away from batch processes towards in-line, high throughput, high yield processing (Candelise 2012).

Learning and cost reduction in manufacturing PV BOS components have been less substantial than for modules, because BOS components are common, mass-produced electrical and mechanical components with mature markets outside the solar industry. Nonetheless, incremental innovation in some BOS components has led to lower manufacturing costs, in particular for inverters which have experienced a learning rate in the 10% range (as measured over the period 1995 to 2002) (Schaeffer *et al*. 2004). In the US, a similar trend has been found for declining labour costs relating to installed PV systems (IPCC 2011). And in the UK, the rapid convergence of UK system prices to those in more developed PV markets also suggests knowledge spillovers across countries i.e. new countries and PV markets learning from other countries' experiences (Schaeffer *et al*. 2004).

Learning via spillover has been a feature of PV crystalline silicon technologies which have benefited from the experience of the already mature semiconductor industry (Candelise 2012). It has also been a feature of the CCGT sector. For example, during the EEC and US restrictions on the use of CCGT generation in the 1970s and 80s, technical learning continued because improvements in aero engine technology continued apace (Winskel 2002). Earlier, in the materials field, the use of supercharger turbines in the late 1950s led to a demand for materials with improved thermal and mechanical properties (Castillo Castillo 2012). This, combined with the use of aeronautical turbo-superchargers, resulted in the requirement for, and further development of, new alloys (Islas 1999) which have benefited CCGT technology.

Indeed, differences in scale and the continuous operation requirements applicable to CCGT meant that, rather than overall design or functionality, it was mainly the advances in fluid dynamics, materials, techniques for calculation, experimentation and manufacturing that eventually benefited CCGT (Islas 1999). In terms of material science, evolution in crystallography took place over several decades and by the mid-1980s the crucial materials had evolved into new alloys suitable for superchargers. The evolution went from super alloys to directed super alloys and eventually to re-crystallised super alloys (Islas 1999).

Learning effects in the CCGT sector continued during the 1980s and much of the 90s, the principal characteristic being the impressive technical progress of the industrial gas turbine, in particular the achievement of major temperature and efficiency increases. For example, in the case of Siemens gas turbines, the turbine inlet temperatures rose from 990°C to almost 1250°C and the combined cycle efficiency from 45% to 55% (Islas 1999). Learning and innovation have continued since then such that combined cycle power plants currently achieve efficiencies approaching 60% (Castillo Castillo 2012).

Finally, even in the case of nuclear, where costs (at least in most OECD countries) have shown a greater tendency to increase than decrease, there is evidence of cost reduction from learning-by-doing. In France for example, one of the likely benefits of the standardisation of design that characterised much of the national nuclear programme was learning-by-repeated-doing and an avoidance of too much 'reinventing the wheel'. It is suggested that this standardisation contributed to a reduction in capital costs of 10-15% (Grubler 2010).

Problems with learning

It is clear from the case studies reviewed in Chapter 4 and the wider review of learning in Chapter 3 that there is a large weight of empirical evidence that demonstrates that learning can occur. However, this does not demonstrate that it is inevitable. As we discuss in the third part of this chapter it can be overwhelmed. Moreover, the rate of learning varies between technologies and across time/technological maturity. This has important implications for the accuracy of technology cost forecasting.

The technical and production maturity of a generating technology and the extent of its deployment are critical to on-going learning. Thus it is argued that the more mature and developed the technology, the less opportunity and potential there exists for further learning and innovation. According to Mott MacDonald (2010), for example the scope for further endogenous learning in the onshore wind sector is recognised as being limited, since onshore wind is now perceived to be a relatively mature technology. Indeed, of the nine drivers of onshore wind cost considered in GL Garrad Hassan (2010), 'scale, learning and innovation' is assigned the lowest magnitude. Similarly, CCGT is a relatively mature technology which is approaching the boundaries of thermodynamically feasible efficiency gains. This maturity limits the scope for significant additional learning and by extension, the same applies to CCS in respect of the underlying gas or coal plant (with the exception of IGCC) (Viebahn *et al*. 2007, Al-Juaied and Whitmore 2009).

Whilst relatively immature technologies have considerable potential for learning and innovation, it can nonetheless take time to reap the benefits and for cost reductions to be realised. Potentially, this applies especially to CCS and arguably still to offshore wind. As Rubin *et al.* (2007b) point out, there is historical precedent for technologies deployed in the power sector to demonstrate cost increases during early commercialisation, before costs fall. And as we discuss in the preceding sub-section, learning rates can change, extrapolations may be inaccurate and a generalised expectation of cost reduction or evidence of learning in a particular technology, is not always sufficient to make accurate cost forecasts within any particular time horizon.

The nuclear case study shows that there are additional ways in which learning may be compromised or even reversed. In the 1970s and 80s, the rapid rate of deployment of nuclear plant and frequent changes in design hampered the industry's ability to apply learning from earlier projects to later ones because projects were running simultaneously, albeit at different stages (MacKerron 1992, Rai *et al.* 2010).

Moreover, Neij (2008) points out that nuclear plants are individually designed and built according to local conditions which restricts the opportunities for cost reduction related to experience. Experience sharing and spillover have been limited by design diversity and customisation as well as being undermined by long lead times in planning, construction and commissioning periods (Thomas 1988). This was particularly the case in France when the industry introduced a new French design that did not easily allow learning spillovers in design or construction (Greenacre 2012a). It was also a feature of the US nuclear industry in the 1970s which, despite the unstable regulatory environment, saw a rapid growth rate in deployment characterised by competitive reactor pricing coupled with optimistic cost projections (MacKerron 1992, Rai *et al.* 2010). The result was that manufacturers frequently changed reactor designs, not only in response to regulatory pressures but also in order to offer customers increased generating capacities. In the US during this time, over 50 utilities began separate procurement programmes involving at least 6 vendors, 20 architects/engineers, and 26 construction contractors. The result was 110 plants, most having unique design and operating characteristics (Rai *et al.* 2010).

Over and above this, the sheer complexities of reactor design and construction in general may also have limited the pace of learning or possibly even reversed it (Grubler 2009). Economies of scale, argues MacKerron (1992), have proved elusive because complexity has increased disproportionately as reactor capacity has grown. Indeed, MacKerron argues that the single most important cause of increases in capital costs during the period from the 1960s to the 1980s was the growing complexity of nuclear plants.

One further aspect to consider regarding the potential difficulties with learning is what may be termed 'knowledge obsolescence' or 'organisational forgetting' where long lived technologies are commissioned on a multi-decadal cycle. Grubler (2010) argues that these problems exemplify how knowledge obsolescence has resulted from an extended period of no nuclear construction experience. Or, as Tolley and Jones (2004) puts it, "if construction is sporadic, learning effects will suffer".

Economies of scale

Scale economies arising variously at the unit, manufacturing and deployment level contribute to capital and levelised cost reductions and together form part of the 'returns to adoption' that forecasters would expect to occur over time.

In the wind sector, upscaling of unit size has been an important factor. Commenting on offshore wind, Milborrow (2003) anticipated cost reductions both from economies of unit scale as well as from technological improvements – a reasonable expectation given that onshore wind turbine upscaling had delivered substantial cost reductions throughout 1980s to mid-1990s. The average size of onshore wind turbines installed in Denmark, for example, increased from 71 kW in 1985 to 523 kW in 1996 (EC 1999). The larger the machines the fewer are required for a given capacity. This brings savings in site costs (thus driving down capex) and in operation and maintenance costs (thus driving down levelised costs) (European Commission, 1999). Also larger turbines, with taller towers tend to capture more wind. This results in increased generation and thus lower LCOE (Lako 2002).

Average installed onshore turbine size in the US rose from 0.9MW in 2001 to nearly 1.7MW in 2008 (EWEA 2009, Bolinger and Wiser 2011) . Whilst this increased size led to increased wind turbine prices on a £/MW basis (since mass scales more rapidly than height, with towers needing to be wider to support the extra height) (Bolinger and Wiser 2011), the impact of increasing wind turbine costs on capex costs is mitigated to a certain extent by decreased balance of plant costs. Again, the effect on LCOE is further mitigated by the higher capacity factors of larger, taller turbines (Bolinger and Wiser 2011).

Economies of scale at the manufacturing level have been evident in the onshore wind sector (Bellarmine and Urquhart 1996) and especially so in the PV industry. Here, the size of module plants has played an important role in reducing costs, and the last decade has seen a dramatic increase in PV production capacity and average plant size. In 2007, average plant size was c.100MWp/y but this has increased to the 500-1000MWp/y range or even more. Meanwhile, thin film PV is considered to have major potential for cost reductions assuming expected increases in production facility sizes (and efficiencies) are realised (Woodcock *et al.* 1997, Zweibel 2000, Chopra *et al.* 2004, Zweibel 2005, Hegedus 2006, EU PV Technology Platform 2007, EU PV Technology Platform 2011). Indeed, the capacities of thin film (CdTe) PV manufacturing facilities have already reached the MW range and thin film modules are currently the least expensive to manufacture. For instance, thin film modules have been produced at a cost of $0.74/Wp by First Solar, a company which has managed to increase production capacity from 25 MW in 2005 to over 2 GW in 2011 (First Solar 2011).

PV, along with wind, can also benefit from economies of deployment scale, allowing certain fixed costs to be spread over greater project size. Moreover with CCS, it has been suggested that economies of scale in the deployment of CCS may be available from a clustered pipeline/transportation network (Jones 2012a).

Nevertheless there is some evidence that economies of scale do not always deliver the cost reductions expected. So-called 'mega-projects' have a unit size and complexity that may carry intrinsic diseconomies of scale. For example in the mid-1960s, the nuclear industry scaled average reactor capacity up from 400-500 MW to about 800MW. Then, before these were even completed, developers began constructing 1100 MW capacity reactors. The logic was that economies of scale would bring costs down, but in reality the frequently changing designs precluded the standardisation that might otherwise have led to economies of scale and replication (MacKerron 1992, Rai *et al.* 2010). As we have seen, it also led to diseconomies of scale arising from increased complexity, lower morale and productivity (due to lengthening construction horizons), and greater demands on management (Cantor and Hewlett 1988).

One of the potential results of project complexity or design change is to prolong lead times and cause substantial delay. For example, NEA (2000) observes that US nuclear plants built before 1979 took an average of five years to build and license whilst those built post-Three Mile Island averaged almost 12 years. In the latter cases, financing and other time-related cost escalations could represent as much as half the total cost (Spangler 1983, NEA 2000).

According to Cohen (1990), US construction times increased from 7 years in 1971 to 12 years in 1980 which, combined with the increase in labour and materials costs, contributed to a quadrupling of capex. Meanwhile, Thomas (1988) notes a clear statistical trend in Germany between 1967 and 1977 towards longer construction periods and higher costs. The predominant explanation is the interaction of regulatory and technical factors, especially reactor type. Similarly, Grubler (2010) argues that in France the move towards a new French reactor design in the 1980s caused lengthening construction times and consequent cost escalations.

The experience of non-OECD nuclear build during the 1990s provides a striking contrast. Tolley and Jones (2004) observed that the plants in construction since the early 1990s - mostly Asian - were built more quickly than in the US and in France, and with less cost variability. Up to the late 1970s when the last US plant began construction, the average construction time in the US was (according to Tolley and Jones) nearly ten years. For plants beginning construction between 1993 and 2001 (i.e. in non-OECD countries), the global average was just over five years and the nuclear case study shows that during this period estimates of contemporary costs were falling significantly.

Economies of scale, argues MacKerron (1992), have proved elusive because complexity in particular has increased disproportionately as reactor capacity has grown. In addition, the large-scale, often one-off nature of nuclear power plants makes it much more difficult to achieve the lower costs associated with manufacturing many (smaller scale) units of the same type, as in the case of PV (Koomey and Hultman 2007). However the impact of such diseconomies may be lessened in cases where multiple reactors are built simultaneously on the same site (Greenacre 2012a).

The diseconomies problem experienced in the nuclear sector may be a special case though it remains to be seen whether coal- or CCGT-CCS will encounter the same difficulties. It is also worth noting that there is an important difference in evolution between CCGT and coal-fired and nuclear generation. The latter two tend to embody historical values typical of very large-scale plant such as security of fuel supply, protection of the domestic industry, pursuit of scale economies.

In contrast, CCGT was developed within a different international industry context. It is associated with different values such as low capital intensity, far shorter lead-times, competitiveness in small units (Winskel 2002). In fact, the absence of significant economies of scale in gas turbines makes it possible to use smaller-scale modular units without their competitive position being undermined by larger scale plants (Islas 1999). The implication of this is that the growing complexity of coal and nuclear power plants, which has introduced "great rigidity into electricity systems and serious diseconomies affecting production costs" (Hirsh 1989), does not apply to CCGT.

To summarise, it would seem that the degree of opportunity for different forms of scale economy is highly technology-specific, historically bounded and cannot simply be assumed across the board. As with learning effects, scale effects can lead to cost reductions, but extrapolation needs to be undertaken with considerable care.

Standardisation or customisation

A theme closely related to the issue of scale economies is that of standardisation (and its converse, customisation). PV module manufacturing, of course, has benefited greatly from standardisation but so too has BOS component manufacture. Here, higher volumes of production, economies of scale, and a shift of system assembly from the field to the factory have all helped to reduce cost (Candelise 2012).

The earlier years of nuclear experience, on the other hand, illustrates the downside of a relative lack of standardisation. Frequently changing reactor designs (predominantly due to competition strategies and response to regulation) have precluded the standardisation that might otherwise have led to economies of scale and replication (MacKerron 1992, Rai *et al*. 2010). In France, Grubler (2010) attributes the worst of the cost escalation to a gradual erosion of standardisation and instead trying to upsize and modify the nuclear reactor design late on in the programme. This involved replacing the 900-1300 MW Pressurised Water Reactor (PWR) designs that had been relied upon for the majority of the programme with 1500 MW N4 reactors. The result was an endogenously-driven "negative learning process" due to inadequate standardisation and additional learning and FOAK costs. Moreover, Neij (2008) points out that nuclear plants are individually designed and built according to local conditions which restricts the opportunities for cost reduction related to standardised experience. Experience sharing and spillover have thus been limited by design diversity and customisation (Thomas 1988).

By contrast, the downwards cost trajectory for nuclear build in the 1990s and early 2000s results in part from increasing standardisation. For example, until late in France's programme the deployment of nuclear power relied on only three standard designs which were reproduced at different locations to enable cost savings (Grubler 2010). Globally, there has been a growing dominance of the light water reactor (LWR) design, and especially the pressurised water reactor (PWR) variant. Worldwide (excluding the then Soviet Union), of the more than 100 reactors under construction in 1986 and therefore completed in the 1990s, 80% were LWRs and this pattern of increasing standardisation has since continued (Kern 2011).

Supply chain and market dynamics

Market supply and demand conditions are also a key endogenous theme albeit one with exogenous aspects as well. The case studies demonstrate that in circumstances where this puts upward pressure on costs we can make a distinction between supply chain bottlenecks and market competition issues.

Bottlenecks are the result of demand growth and a lack of adequate supply response, whether with regard to materials, components, specific skills or labour. Competition issues arise when there are only a limited number of companies in a particular market thus allowing the potential exercise of oligopolistic power.

Regarding this latter point, in the case of UK offshore wind we have already noted the possible impact on competition given the limited number of companies engaged in turbine manufacturing for the offshore industry (BWEA 2008, Carbon Trust 2008, Ernst & Young 2009, RAB 2009).

A related factor is that offshore turbines so far occupy a small niche relative to onshore turbine markets and it is understandable that a 'niche premium' would in any case attach to the offshore market (Greenacre *et al*. 2010). A not dissimilar situation currently exists in the nuclear industry where there are only two companies – Japan Steel Works and Creusot Forge in France – that have the forging capacity to create the largest components for nuclear plants (Grimston 2012b).

Turning to supply chain bottlenecks, several of the case studies examine the effects of input constraints giving rise to a so-called congestion premium. For example, in the mid- to late 2000s, supply chain constraints in the onshore wind industry contributed to escalating capex prices although the congestion premium has since reduced (Mott MacDonald 2010, Mott MacDonald 2011).

Shortages were experienced for a range of components such as bearings, generators, hubs and main shafts (de Vries 2008) and the problem was particularly pronounced for gearboxes (Blanco 2009). Bottlenecks were experienced by both turbine manufacturers and sub-contractors, and were compounded by difficulties in obtaining construction equipment (de Vries 2008, EWEA 2009).

A key cause of such bottlenecks was the boom in demand for wind turbines in North America particularly due to the US Production Tax Credit (PTC), and also in Europe and Asia (Blanco 2009, EWEA 2009, GL Garrad Hassan 2010). As such, there was insufficient turbine production to meet this strong demand (IEA 2006). In addition, Bolinger and Wiser (2011) suggest that tight supply and the rapid pace of deployment also had the effect of causing short-term increases in labour costs as the supply of available labour struggled to keep up with demand.

Competition in the onshore sector had a knock-on effect on the offshore sector, delaying European projects and forcing up prices Gordon (2006). Indeed, Douglas-Westwood Limited (2008) reported that the combination of a strong market and constrained supply drove onshore turbine prices upwards by 30% between 2006 and 2008. Offshore turbines are usually marinised versions of onshore ones and by 2007 turbine supply was the dominant bottleneck. The UK offshore sector was squeezed by onshore turbine demand from China, India, and elsewhere in Europe as well as by a US market fuelled by the PTC (BVG Associates 2007), and the situation may have been exacerbated by the oligopolistic nature of the UK offshore turbine market (see earlier comment in this sub-section).

In the nuclear industry, strong demand for generation plant over recent years has resulted in supply chain issues, longer delivery times, and cost increases as manufacturers have struggled to meet demand. Nuclear plant operators have also been competing with oil, petrochemical and steel companies for access to resources. Thus, as with the two competing wind industries, both competition from within the sector and with associated industries has been a cost escalator and is likely to further increase costs and delays if worldwide nuclear activity expands (Grimston 2012b).

In the CCGT sector supply chain bottlenecks over recent years have significantly increased engineering, procurement and construction (EPC) prices. Full order books for vendors and manufacturing capacity constraints have increased prices for plant components (Mott MacDonald 2010), and caused delivery delays that have increased project financing costs (Chupka and Basheda 2007). Granted, these bottlenecks have affected the price of the underlying generating plant rather than that of CCS technology itself, nonetheless this market congestion has led to an increase in overall price estimates for CCS-fitted power plants. In particular, since advanced supercritical coal plants have been particularly vulnerable to supply chain bottlenecks, the effect on post-combustion coal CCS projections has been especially pronounced. Indeed, Mott MacDonald (2010) suggested a congestion premium of almost 17% on top of estimated 2010 capex.

Turning to PV, as with the US PTC's effect on the wind industry, so too national policies have impacted the PV sector. In the mid-2000s, demand pull policies – primarily Feed-in Tariffs (FiTs) were implemented in key European countries such as Germany and Spain. The resultant sudden increase in demand for PV modules caused a serious supply chain bottleneck in the form of a silicon feedstock shortage (Candelise 2012). This caused silicon spot prices to go up from $50/kg to over $500/kg in 2008 (Flynn 2009), increasing PV production costs and leading to an inversion in the historical module price reduction trends.

However, there has been a dramatic drop in prices in the last two years. In response to the supply shortage, new investments in feedstock production (as well as increased R&D efforts) led to production capacity expansion which eventually created oversupply in the silicon feedstock market. This has pushed silicon prices downwards (spot prices were around $35/kg in late 2011 (Campbell 2012, Iken 2012)) and has been a driver of the dramatic module price drop experienced in the last couple of years whereby average c-Si module prices have fallen by more than 45% from mid-2010 to March 2012 (Solarbuzz 2012).

Supply chain bottlenecks may not only be confined to key components and resources. As the nuclear case study demonstrates, specific skills shortages have on occasion helped to push up costs as well. We treat this as an endogenous factor since it is arguably within the powers of the vendors and utilities to address the problem through more training. In the 1970s, the growth in reactor orders created a skills shortage in the US (Thomas 1988). More recently a skilled labour shortage worldwide has again been a factor in causing cost estimates for major construction projects to rise. In North America, for example, skills shortages in both nuclear design and construction personnel have been expected to delay construction schedules and drive up projected costs (Ahearne 2011; Grimston 2012b). Meanwhile, in the UK, skills shortages have been highlighted for some time. A 2006 report from the UK Trade and Industry Select Committee suggested that new build programmes worldwide, particularly in Asia, would result in the relatively small UK market facing stiff competition for skills from other countries (HoC 2006). At the EU level, it has been estimated that demand for skilled labour will increase by up to 170% by 2018 if all planned new nuclear builds were to be built (Kruse *et al.* 2010).

Similarly, in the onshore wind sector the necessity to have a dedicated supply chain for each new and larger turbine power rating had the effect of causing short-term increases in labour costs as the supply of labour struggled to keep up with demand (Bolinger and Wiser 2011). This shortage of labour in the onshore wind sector was exacerbated by the rapid rate of deployment, something that the case studies show can have conflicting effects.

In the medium to longer term, greater deployment should lead to lower costs. In the shorter term however, it can lead to temporary upward pressure on costs as was the case in the PV sector, and also in the nuclear industry during the 1970s and 1980s when the rapid rate of deployment put considerable pressure on contractors who until then had little experience in the business (MacKerron 1992, Rai *et al.* 2010). Thus, technology roll-out runs the risk that excessive rapidity and scale of deployment may result in supply chain bottlenecks and a consequent congestion premium. The CCS case study cautions that this is a phenomenon that is sometimes overlooked by future costs forecasters.

Regulatory environment

Regulatory conditions are potentially relevant to costs and cost forecasting for all the generating technologies but have been particularly applicable in the wind sectors (in the UK) and especially in the nuclear industry. In the future, they are likely to be highly relevant to CCS as well.

In both the on and offshore wind sectors, for example, planning consent issues in the UK have proved problematic. By the early 2000s the planning process for UK onshore wind projects was emerging as a major factor limiting the rate of deployment. The difficulties and costs experienced by many onshore developers in gaining planning permission stemmed from concerns amongst local communities about the impact of wind turbine siting (PIU 2002b). Moreover, one of the effects of this was to stimulate the move offshore as it became clear that the offshore option offered the potential for greater public acceptability, chiefly because of the lower visual impact (PIU 2002a). This in turn meant that it would be possible to build much larger turbines than might be acceptable on land (DTI 2002a).

However, regulatory burden also then impacted UK offshore development. Consent delays affected UK Rounds 1 and 2 such that the typical timeline for a large UK project is estimated to be between seven and nine years, in large part due to the complexity of the planning process. This has put pressure on project finance and recoupment, and has also placed strain on the supply chain since lengthy delays undermine confidence (Greenacre *et al.* 2010).

Problems in the wind sectors have nevertheless been dwarfed by the regulatory burdens experienced by the nuclear industry. Over several decades, many analysts and commentators have observed that the escalation in costs from the start of commercial reactor construction in the mid-1960s through to the late 1980s in large measure stems from the endogenous effects of an unstable, changing regulatory environment (see, for example, Cantor and Hewlett (1988); Hultman *et al.* (2007); Neij (2008); Rai *et al.* (2010). This has been especially apparent in the US to which much of the evidence and cost data refers. In large part, this reflects the fact that, due to concerns about accident and waste disposal (and also proliferation), nuclear power is in a different safety category than other generating technologies (CCS notwithstanding, which is addressed below).

By the late 1960s nuclear safety and waste disposal was the subject of increasing public focus and had become a predominant theme for the environmental movement (Rai *et al.* 2010). Direct action, political lobbying and the use of legal action introduced major delays into projects and interrupted operations (Grimston 2012b). In large part this fostered an unstable regulatory climate in which the rules kept changing in apparently arbitrary ways (MacKerron 1992). Public and political opposition to nuclear power continued to grow through the 1970s and 1980s and whilst there was already an underlying pressure for more stringent regulation, a number of crises increased the uncertainty and upward pressure on nuclear costs (Grubler 2010, Grimston 2012b). In the US, these were the 1975 Browns Ferry incident and the 1979 Three Mile Island accident, and later in the Ukraine, the 1986 Chernobyl explosion.

The consequence of all this was the repeated call for design changes, with regulators demanding more safety features in such areas as fire protection and seismic criteria (NEA 2000). In many cases these had to be back-fitted after construction had already begun causing additional material, equipment and labour costs, together with significant delays, which added to the costs of finance (Tolley and Jones 2004, Rai *et al.* 2010, Grimston 2012b). According to Tolley and Jones (2004), regulation was responsible for a 69.2% increase in capital costs from 1967 to 1974 and may have resulted in approximately a 15% per annum increase in plant costs during the 1970s and 1980s (with the caveat that other effects may have been contributing as well).

A contrasting example of the effects of regulation is provided by the declining costs experience between 1990 and the mid-2000s when nuclear project activity dried up in the west but was taken up in a number of non-OECD countries. Along with lower input costs, the likely drivers behind these cost reductions included a less stringent, cost-forcing regulatory environment in Eastern Europe and Asia which also resulted in significantly shorter project durations. In addition, these non-OECD countries showed a greater incidence of command-and-control type economies which were likely to ensure stable electricity prices and therefore lowered the risk premium on capital financing (Grimston 2012a).

Regarding the estimation of future costs, it is not difficult in principle for forecasters to acknowledge the importance of the regulatory environment on costs. However, envisaging exactly how the effects might play out over-time and how they should be quantified is much more difficult.

Policy environment

Government policy can have both positive and (at least temporary) detrimental effects on a generating technology's deployment and cost trajectory. In the UK for example, both on and offshore wind deployment has benefited from the introduction in 2002 of the Renewables Obligation, a certificate trading scheme that places a mandatory requirement on electricity suppliers to source an increasing proportion of electricity from renewables (see for example (DTI 2007)).

In the CCGT sector, the privatisation of the UK's electricity supply industry in the late 1980s and early 1990s was a critical driver of the so-called 'dash for gas' which contributed to deployment, learning, and resultant cost reductions (Castillo Castillo 2012). By contrast, the policies that restricted the use of natural gas for power generation had a significant negative impact on deployment rates and contributed to the decoupling of the efficiency improvement trajectory from that of generation costs. The temporarily restrictive policies were, in Europe, the Directive 75/404/EEC on the restriction of the use of natural gas in power stations, and, in the US, the Powerplant and Industrial Fuel Use Act of 1978. The former was removed in 1991 and the latter in 1987, see Castillo Castillo (2012).

Meanwhile, the PV sector has benefited from policy incentives implemented in key countries such that worldwide installed capacity has grown from 1.4GW in 2000 to over 67GW in 2011 (EPIA 2012). This policy-driven market growth has triggered significant module price reductions, with especially dramatic price drops in the last couple of years. In Germany, policy support was introduced in the mid-2000s via Feed-in Tariff (FiT) schemes in conjunction with 'soft loan' schemes to stimulate demand. Similarly, Italy first implemented FiTs in 2006 and started experiencing a major market expansion in 2008 to become the world's largest PV market in 2011. In the UK the recent introduction of a FiT scheme has stimulated its PV market leading to a substantial increase in installed capacity since its implementation in April 2010. The result has been considerable reductions in UK system costs (Candelise 2012).

The downside of such policies is the risk of creating a supply chain bottleneck with a consequent congestion premium. For example, the sudden increase in demand for PV modules due to demand pull policies created an acute silicon feedstock shortage, increasing production costs and leading to an inversion in the historical trend of module price reduction (Candelise 2012). See also earlier sub-section on 'supply chain and market dynamics'.

As with the overall regulatory environment, the challenge for costs forecasters is to envisage how the effects of policy intervention might play out over time, and to estimate both the quantitative impact of policy on costs and the likely duration of potential bottlenecks.

5.4 Exogenous themes

As noted, exogenous themes address those cost issues that are largely beyond the ability of either the actors involved in a generating technology or policymakers more generally to influence or mitigate them. The six case studies consider a variety of exogenous themes with the potential to impact capital and/or levelised cost trajectories and which therefore tend to adversely affect the accuracy of future costs forecasting. We categorise these exogenous themes as follows:

- Commodity prices
- Labour costs
- Interest rates & financing costs
- Exchange rates
- Exogenous policy effects

Commodity prices

In the period from the mid-2000s until around 2010, rising commodity prices pushed up the capital and levelised costs of all the generating technologies with the exception of solar PV. Largely unanticipated by costs forecasters prior to this period, the cost escalation of essential raw materials contributed greatly to disparities between earlier cost projections and actual outcomes.

In both wind sectors, increases in steel, copper, and cement prices have been one of the principal drivers of rising costs. For onshore wind turbines, the steel used in towers, gearboxes and rotors, constitutes around c.65-80% of total turbine mass (Blanco 2009, Bolinger and Wiser 2011) whilst copper is used in generators and cables, and cement is used in onshore foundations (Blanco 2009). In the offshore sector, steel typically accounts for around 12% of total project cost (BWEA and Garrad Hassan 2009). From 2002 to 2007 the global steel index experienced growth of 47% CAGR (Ernst & Young 2009) and as a result the increase in steel prices was a contributing factor to offshore turbine and tower costs rising from £0.9 million to £1.5 million/MW (a 67% increase) in five years (RAB 2009). Steel price rises played an even greater role in the escalating costs of foundations which increased from around £250,000 to £700,000/MW (a 180% increase) over the five years to 2009 (Ernst & Young 2009). The cost of other relevant commodities, such as copper and cement, also increased and analysis by The Carbon Trust in 2008 suggested that if commodity and materials prices were to return to 2003 levels, overall offshore wind power costs would have fallen by 11% (Carbon Trust 2008).

Similarly, commodity price volatility has impacted nuclear capex, CCGT capex, and also the cost projections for CCS (though largely because of the increased costs of constructing coal- and gas-fired power plants rather than specifically CCS technology) (Davison and Thambimuthu 2009, Harris *et al.* 2012). The different generating technologies are, of course, not only competing with each other for raw materials such as steel and cement but also with other industries. In addition to the direct cost effects, power plant constructors may have also had to suffer delivery delays which pushes up indirect costs such as financing (Grimston 2012b).

Since the economic downturn, commodity prices have declined (DoE/NETL, 2010). In 2008, the steel index fell by 58% returning to the long-term historic trend, and the commodity prices index fell by 5% CAGR, although it remained substantially above the historical trend line (Ernst & Young 2009). Nevertheless, despite the price declines, there is a time lag before they feed through to benefit capex costs (Wiser and Bolinger 2009). For fossil fuel technologies, fuel price fluctuations also have a substantial impact on costs.

The levelised costs of CCGT and the estimates for coal and gas CCS are highly sensitive to fuel prices (Mott MacDonald 2010).With CCGT, levelised costs depend very heavily on the trajectory of gas prices, moreover underlying gas prices from different sources can vary considerably even for the same year (Castillo Castillo 2012). Levelised cost estimates for CCS are also contingent upon future gas or coal prices (Davison and Thambimuthu 2009). The case studies indicate that fuel price escalations were not anticipated prior to their emergence in the early 2000s. They represent a particularly profound confounding variable in analysis of the future cost of energy from CCGT plant, with or without CCS.

Labour costs

Fluctuations in general labour costs (as opposed to specific endogenous skills shortages) can also contribute to the challenge of accurate forecasting. A case in point is the nuclear industry where increases in labour costs were one of the factors that caused capex to quadruple in the US between 1971 and 1980 (Cohen 1990). In the period 1976 to 1988, nuclear costs increased at an average rate of 13.6% per annum compounded whilst labour costs increased 18.7% and materials costs only 7.7% (Cohen 1990). Conversely, during the 1990s and early 2000s when nuclear costs were falling, a significant cause of this was lower input costs – especially labour costs – due in part to a slowing down of the world economy and also the shift of nuclear construction to the cheaper labour markets of Asia and eastern Europe (Grimston 2012a).

It is also possible that labour costs across countries may not be fully factored into analysis of trends. During the 1990s and early 2000s, for example, nuclear cost projections in OECD countries were falling along with the estimated outcomes from non-OECD countries. Assumptions about costs within the developed countries where little or no construction was occurring were likely being influenced by the numbers emerging from the lower cost environments where construction was actually taking place (Grimston 2012a). Tolley and Jones (2004), for example, pointed to the experience in Asia as offering a "basis for optimism regarding future construction" in the US, especially with regard to reduced construction times. And in the UK, as late as 2006, when nuclear cost estimates had already started to rise again, Mackerron (2006) reported that recent UK-applicable estimates appear to have derived from studies designed to apply to other countries.

Interest rates and cost of finance

Macroeconomic factors effecting background rates of interest on loans and other forms of finance can affect project costs quite significantly, particularly if construction times are long. Of course, policy can help reduce risks and hence the cost of capital, but our focus here is not on project/energy specific risk adjusted rates of return but on the wider macroeconomic context. Whilst interest rate volatility is applicable to a greater or lesser extent for all the technologies, it particularly affects larger scale projects with long completion horizons, where financing costs during construction greatly affect total capital costs. According to Tolley and Jones (2004), by the time a new plant comes on line, total capital cost can be 25% to 80% greater than the overnight costs, depending on interest rates and length of construction period.

To illustrate, Spangler (1983) reported that the economics of nuclear power were impacted by the high interest rates prevailing during the late 1970s and early 1980s, especially when construction schedules were also subject to significant delays. In 1976/77 US Federal prime rates ranged between approximately 6% and 8% per annum. By 1980/81 rates had hit a record high of around 21% and in 1983 were still 11% or more (FedPrimeRate.com 2012). During most of that decade rates remained relatively high such that MacKerron (1992) considered interest rates to be a highly important exogenous factor affecting costs. Furthermore, after the 1979 Three Mile Island accident, financial markets reduced the bond ratings of US utilities. This meant that their borrowing costs rose, thereby increasing the interest during construction (IDC) component of total cost (Thomas 1988). Thomas presumed that nuclear project financiers elsewhere in the world also took note thus impacting financing costs worldwide.

Similarly, the offshore wind case study notes that the cost of finance has been an exogenous driver of the rising costs trajectory. In theory, if offshore wind developers use project finance then the increasing experience in construction and operation should gradually reduce the risk premium for offshore development resulting in a decreasing cost of capital (Greenacre *et al.* 2010). However, utility developers, who have been responsible for the majority of capacity installed to date, have instead typically used balance sheet financing (Ernst & Young 2009). The problem with this has been that spreads for utility bonds from mid-2007 onwards rose markedly because of the crisis in the global credit markets resulting in a higher cost of corporate debt (Ernst & Young 2009).

Again, as with many of the endogenous and all of the exogenous themes, financing costs are very challenging to forecast even though they are of fundamental importance. That said, the current interest rate environment makes the situation somewhat easier, at least for short to medium term projections. Rates may stay approximately the same or they may rise, but it is difficult to envisage how they can go much lower.

Exchange rate

From the UK's perspective specifically, the fluctuation in the value of Sterling versus other currencies – the Euro especially – is an exogenous theme which has been particularly relevant in the wind sector in the period immediately prior to the writing of this report. For onshore wind, the weakening of Sterling against the Euro during the 2000s significantly elevated prices for UK projects, which have typically been dominated by European imports (GL Garrad Hassan 2010). Indeed, some commentators view currency movements as one of the most significant drivers of increasing onshore wind costs in the late 2000s (Arup 2011, Bolinger and Wiser 2011).

The Euro/Sterling exchange rate also contributed significantly to the rise in costs borne by UK offshore wind developers. Around 80% of the value of a typical UK offshore wind farm is imported and has either been priced in Euros or priced in a currency tied to the Euro (Greenacre *et al.* 2010). Since 2000 when the exchange rate was approximately €1 = £0.60, the Euro gradually increased in value against Sterling, reaching almost one-to-one parity in December 2008. Consequently, until 2009 UK developers experienced continued increases in component costs because of the Euro's gradual appreciation. In addition, vessels and support services have been largely sourced from continental Europe, hence installation costs also rose, and O&M costs have also been adversely affected (Ernst & Young 2009).

Both on and offshore cases also illustrate how positive cost effects from one driver may be counteracted and outweighed by another. Consequently, whilst prices for commodities have fallen since 2008 as a result of the global downturn any positive effect on UK costs has until recently been more than offset by the appreciation of the Euro against Sterling (Ernst & Young 2009).

5.5 Conclusions

This review shows that the cost of electricity generation can fall through time and as deployment rises. The review revealed considerable empirical evidence of cost reduction, in many technologies. It also revealed a detailed and sophisticated discourse related to the use of learning curves. Analysts are seeking to improve the predictive value of learning curve analysis, and interrogating the other facts that drive cost reduction. Our understanding of learning as a phenomenon is becoming more sophisticated. The literature appears to pay less attention to the methodological issues associated with engineering assessment, but does not challenge its usefulness. Overall, it is clear that engineering and learning/market based approaches offer complementarities and are best seen as partners in the quest to better understand cost reduction potential. Both need to be treated with caution, their use carefully qualified, with the central methodological and empirical uncertainties made plain.

Fuel, commodity prices and supply chain issues can have large impacts. The technology case studies reveal a substantial disconnect between cost projections and out turns in the mid-2000s period and onwards. A general trend upwards (PV is the exception to this rule) during the 2000s was not anticipated at all. Gas price increases were not foreseen, neither were commodity price movements and other exogenous factors which overwhelmed downward cost trends previously seen in several technologies and anticipated in others.

Despite uncertainties, recent studies of energy technology costs show improved 'appraisal realism'. The scope of cost estimates (for example what is and is not included) and the assumptions regarding other key variables (such as the discount rate) tend to be well documented in recent analyses. Many recent studies explicitly take account of a variety of factors able to drive costs in the wrong direction. Nonetheless, many contemporary forecasts anticipate a return to cost reductions over the forthcoming years and decades even where costs/estimates of costs have risen. In part this reflects an expectation that factors such as commodity price movements or supply chain constraints will ease and underlying learning effects will lead to cost reduction, particularly through capital cost reduction and efficiency/performance improvement (the cost of fossil fuels remains uncertain and many projections expect them to stay high relative to historic norms).

The case studies also reveal a widely divergent picture of cost trends between the principal technologies reviewed for this report. The trend for PV has been most resolutely downward, albeit from the highest base. Wind technologies and CCGT have also seen consistent and substantial cost reductions, although the cost of both turned upwards, for different reasons, during the mid and late 2000s. The literature on nuclear provides a great deal of insight into why costs have tended to rise rather than fall, at least in the European and US context. CCS remains largely hypothetical at the time of writing, though the literature demonstrates increasing attention to detailed plant design. The offshore wind case study provides a variety of insights both methodological and empirical. In this instance exogenous factors over-rode learning, but the potential for learning in the early stages was also overstated and endogenous factors were not fully factored in.

One size does not fit all. Technology specifics are paramount to cost reduction prospects. Forecasters need to be alert to the specific characteristics and thematic distinctions of the different technologies and their particular physical, commercial, and regulatory environments. For this reason the use of 'proxy' learning imported from other sectors (even similar ones) needs to be treated with caution. The review also suggests that modularity, scope for mass production, and scope for technological innovation make on-going cost reduction more likely. Inherent complexity, a significant need to realise project-level economies of and the need for substantial regulatory complexity make cost reductions more difficult to realise.

Some of the uncertainties revealed by the case studies are exogenous, inherently unpredictable and may exhibit high volatility. Yet these risks are difficult to anticipate, quantify and predict rather than being impossible to image. They are 'known unknowns' and may be investigated and mitigated by the use of numerical ranges and scenario analysis. A key lesson from this is that 'sideswipes' are perhaps inevitable, and can overwhelm cost projections even in the best of analytical worlds, albeit perhaps temporarily.

Other cost drivers are endogenous, more 'known' and therefore lend themselves more readily to future projection. It is, for example, reasonable to expect cost reductions over time to accrue from returns to adoption such as learning effects, on-going innovation, scale effects, and standardisation. It is also possible to anticipate and manage factors such as short term bottlenecks and supply chain constraints. This has important implications for policy design such as time horizons and sequencing.

Initial roll-out of a technology may result in short-term supply chain bottlenecks, 'teething trouble' and difficulty realising anticipated cost reductions – in the short term costs may rise before they can fall. There is historical precedent for technologies deployed in the power sector to demonstrate cost increases during early commercialisation before supply chains and learning from experience are firmly established. The offshore wind case study notes the tendency for the earlier cost forecasts in that sector to focus on cost potential, rather than on the pragmatic challenges of scaling up a supply chain, and avoiding bottlenecks.

Market growth is a necessary but not necessarily sufficient condition for learning and cost reduction. The review reveals the multi-dimensional nature of both projecting future costs and creating the conditions for costs to fall. The potential for spill-overs literature on learning by research indicates that continued attention to RD&D is an essential accompaniment to market enablement. Regulatory constraints also need to be addressed and policy may also be able to facilitate cost reduction through supporting the skills base and ensuring effective sequencing of projects.

Overall, this review reveals a large dataset on technology costs (past, present and future) and a rich and complex literature that discusses the factors that affect cost trends over time. Our understanding of cost reduction forecasting is undoubtedly improving through time, in part through learning from significant failures to anticipate changes to cost trends in the recent past.

We know with confidence that costs can fall, and that given the right conditions 'learning' can make this happen. The role of policy in driving cost reduction comes through very clearly in several of the case studies. However it is less straightforward to be confident about the extent to which they will fall in a particular period in time, and policy can have multiple impacts, for example regulatory complexity can also militate against cost reduction. Cost reduction projections are difficult and challenging and often proved wrong. Perhaps the key challenge is in representing and communicating uncertainty – what is known, not known and unsure in an uncertain world – to decision makers seeking certainty.

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Annex

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Relevance rating for sources

- A rating of 1 indicates that the piece of evidence deals very clearly with one or more aspects of the research questions.
- A rating of 2 indicates that although the paper is relevant, its findings are presented in a way that could preclude direct comparison with other results.
- A rating of 3 indicates limited relevance and/or clarity.
- A rating of 4 denotes papers that are duplicative or, on closer inspection, were deemed not relevant.

Technology case studies

CCGT case study: Ref. UKERC/WP/TPA/2013/008

CCS case study: Ref. UKERC/WP/TPA/2013/004

Nuclear case study: Ref. UKERC/WP/TPA/2013/005

Onshore Wind case study: Ref. UKERC/WP/TPA/2013/006

Offshore Wind case study: Ref. UKERC/WP/TPA/2013/007

PV case study: Ref. UKERC/WP/TPA/2013/009

All available from www.ukerc.ac.uk/support/tiki-index.php?page_ref_id=2863

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