# Technology Change and Energy Systems: Learning Pathways for Future Sources of Energy


**Mark Winskel[1], Nils Markusson, Henry Jeffrey, Sophie Jablonski, Chiara Candelise, David Ward, Paul Howarth.**


**DRAFT PAPER**


## Abstract

There is pressing need to understand the potential of emerging low carbon energy supply technologies, and the learning processes (or effects) associated with them. In particular, analytical approaches are needed that are able to balance simplification (to allow comparisons between technologies), and complexity (to recognise technology specific enablers and barriers). In addressing this issue, this paper firstly briefly reviews existing tools used to compare emerging technologies, especially learning curves and learning rates. Then, drawing on expert accounts of learning effects for several emerging low-carbon energy supply technologies, a novel framework based on 'learning pathways' is developed. A learning pathways framing enables cross-technology and inter-temporal analysis of learning processes. Finally, research themes are identified to further elaborate the learning pathways approach.


## 1. Introduction

### 1.1 The research problem

The increasing urgency of climate change mitigation has focused attention on energy system transformation so as to achieve radical reductions in carbon emissions. One of the key dynamics – and uncertainties – associated with this transformation relate to the development and deployment of low carbon energy supply technologies.[2]

After a long period of decline in energy R,D&D activity globally, associated with economic liberalisation, there has been an upswing in such activity in recent years, and there is now a number of emerging supply technologies at various stages of development, each supported by particular policy initiatives, investment programmes, developer firms and research institutions. Making sense of this activity – in terms of systematic ordering, and judging its effectiveness – has become a major research challenge, and effort, in its own right (see, for example, IEA/OECD, 2006, CEC 2007, DTI, 2007). This is an inherently multi-disciplinary research challenge, spanning detailed technology-specific expertise, and system-wide knowledge and comparisons.

Despite a significant expansion of multi-disciplinary energy systems research in recent years, our present levels of understanding of technological innovation in the energy sector – and how to best manage the inevitable uncertainties involved – remain limited. A range of tools are drawn on, including technology roadmaps, energy system


[1] Corresponding author, email: mark.winskel@ed.ac.uk


[2] The focus of attention here is on centralised energy supply options. This is not to discount other important aspects of system transformation, including system reconfiguration, microgeneration and a range of demand-reducing technological and behavioural opportunities.

models and scenario planning techniques. Each has its strengths. Technology-specific roadmapping exercises are able to identify (and link together) the R,D&D challenges involved in commercialising new technologies. System modelling enable comparison between technology options, and between different possible portfolios of technologies in an overall energy mix. Scenarios allow more space for explicitly considering alternative possible system futures, and the impact of wider social and economic trends and potential disruptions.

All of these tools are limited in their ability to capture and compare the potentials and uncertainties associated with early-stage technologies. Roadmaps are capable of elaborating technology-specific enablers and barriers in some detail, but may overlook competition (and synergies) between technologies. Roadmaps may also lack comparability, in articulating varied levels of ambitiousness across different research communities, or differ significantly in terms of their method and content. Energy system modelling and scenarios offer standardised comparisons, but typically only allow for rather crude representations of innovation activity in emerging technologies on the basis of a small set of parameters, such as capital and operating cost, resource availability and conversion efficiency. Innovation processes (or learning effects) are often represented by a single parameter – the *learning rate* – which may disguise important differences between technology-specific learning effects.

The (necessary) simplifications and abstractions of system modelling have their dangers. Not least, they risk projecting an image of energy policy, in the realm of supply-side options, as a matters of choosing between competing technology options which can be made straightforwardly comparable. Portfolios of future supply mixes can then be assembled on the basis of their superior economic and technical metrics, even though these data are, often inevitably, only weakly grounded in research evidence. Recognition of the uncertainties embedded in such projections may be underplayed.

Alongside these modelling approaches, there is a body of social science-led research, under the banner of innovation studies, which highlights the many enablers and barriers shaping the emergence of new energy supply technologies. These mainly qualitative accounts are informed by conceptual frameworks such as technological innovation systems (Jacobsson and Bergek, 2004; Jacobsson et al., 2004, Hekkert et al., 2007; Bergek et al., 2008) and the multi-level perspective (Geels, 2004; Geels and Schot, 2007). Typically, they reference the range of actors and institutions involved in sociotechnical change, and distinctive types of learning processes, such as learning-by-doing, by-interacting and by-researching.

Clearly, there is a trade-off here between sensitivity to technology-system specifics, and the abstractions and generalisations needed to enable cross-technology comparisons and system planning.

### 1.2 Paper Themes and Outline

This paper reports some of the findings of a cross-disciplinary research group of the UK Energy Research Centre (UKERC) on Learning Effects and Rates for emerging energy supply technologies. UKERC's Learning Effects Working Group (LEWG) was established with the following aims:

- to identify and characterise key learning processes for a number of emerging energy supply technologies
- to highlight the main issues associated with the representation of these processes in cost and performance, as used in system-wide modelling exercises
- to develop a common method for assessing learning effects for early-stage energy supply technologies
- to define the insights (and limits) associated with cross-technology analysis of learning effects for emerging energy supply technologies

A starting point for our work has been recognising the need to strike a balance between attention to specifics, and abstraction and simplification to enable system-level assessments. This led to us to develop a novel analytical tool, or framing device, to enable cross-technology comparisons, while still capturing important technology-specific differences of content and context: the *learning-pathways matrix*.

UKERC's LEWG brings together expertise across a number of emerging energy supply technologies. The work of the Group has progressed in the following steps:

1. An extensive review was undertaken of the learning effects and rates research literature, as it applies to energy supply technologies and energy systems modelling. (Over 100 research papers and reports were reviewed.)

2. The principle learning effects for several different energy supply technologies were characterised using qualitative statements, 'stages of development' analysis, and component analysis. Commentaries were also provided on the representation of technology-specific learning processes in learning rates and modelling exercises.

3. Drawing on the above contributions, a 'learning pathways' (LP) matrix was then constructed to allow for comparisons between the learning systems of different technologies, in terms of their historical development, current status and prospects.

Each of these steps are described in more details below. Firstly, Section 2 offers a brief review of the difficulties associated with learning curve and learning rate analysis for emerging energy technologies. Section 3 summarises the technology-specific contributions on learning effects from the UKERC Working Group. Section 4 introduces the learning pathways matrix, and highlights some of the initial insights it has provided. Finally, Section 5 summarises the paper and identifies issues for further research.

## 2. Learning curves and learning rates

Discussions of future energy supply mixes often refer to the commercialisation of emerging energy technologies with reference to learning curves. Typically, these use a single aggregated *learning rate* to show a progressive decline in unit costs of generation technology over time (more correctly, with cumulative deployment) (see Figure 1, below).[3]

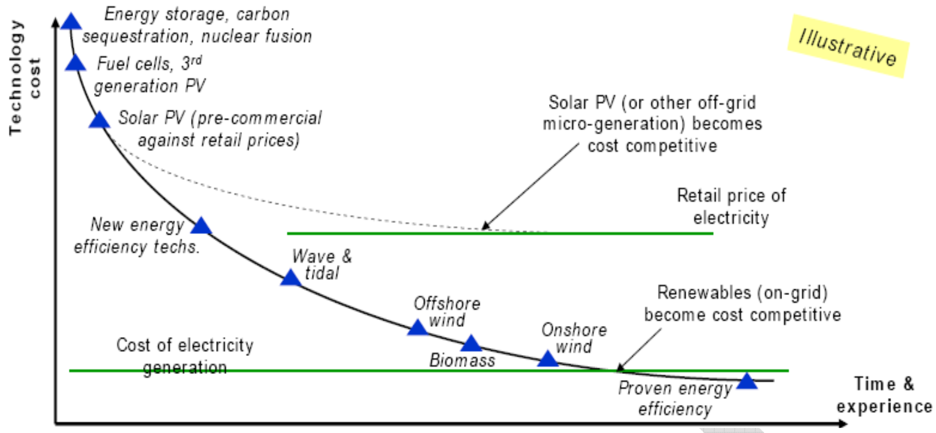


**Figure 1: Idealised Cost Curve for Energy Supply Technologies (Grubb, 2006)**

The process of developing learning curves can be seen as an attempt to represent and condense-down complex sociotechnical processes into a single modelling parameter, the learning rate. Learning rates are appealing because of their apparent ability to capture and quantify technological change, and project it forwards – allowing system-wide modelling exercises to take account of technological learning.

The 'headline message' from learning rate representations of innovation is straightforwards: given sufficient investment in deployment, learning-by-doing will drive down unit costs over time towards commercialisation. Indeed, given some initial cost data, learning curves can be generated and extrapolated so as to calculate the 'learning investment' required to achieve cost-competitiveness with existing, mature technologies.

In practice, innovation processes are less predictable and manageable than this suggests, and given the specificities and complexities involved, our attempts to compare different technologies on the basis of learning rates are likely to disguise important differences. As is recognised in the research literature, applying learning rates for long-term energy system projections is problematic (see, for example, Neij et al., 2003; Nemet, 2006; Jamasb and Köhler, 2007; Söderholm and Sundqvist, 2007; Neij, 2008). Some of the difficulties here include:

- the presumed correlation between market growth and cost reduction cannot be assumed *a priori*. Case study research includes examples of energy

[3] The learning rate is the percentage reduction in unit costs associated with each doubling of installed cumulative capacity. Figure 1, above is an illustrative curve, with the same learning rate used for all technologies. In practice, energy system modelling uses technology-specific learning rates based on research evidence.

technologies which fail to lower costs over time and with deployment, despite significant spending on development programmes.

- even where a correlation is observed, the direction of causality may be unclear. Different learning processes mean that cost reductions may *result* from market growth (via learning-by-doing), or be a *driver* of market growth (via learning-by-research).[4]

- using a single learning rate for an emerging technology field is likely to disguise significant diversity in terms of *place*, *time*, and *content*:
    - despite a trend toward liberalisation and globalisation of energy systems, learning effects and rates still exhibit considerable geographic diversity, across regions, nations and organisations.
    - even under stable economic and institutional conditions, learning rates may be expected to vary significantly over time, as technologies pass through different stages of development (see Figure 2, below). Especially in a context of raised demands for energy system transformation, there is a need to allow for actual or potential discontinuities, step-changes or radical breakthroughs.

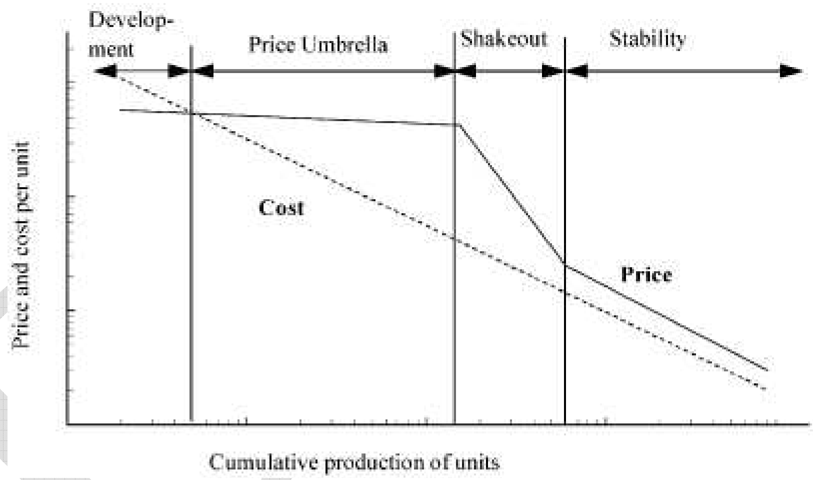


**Figure 2: Idealised Learning and Phases of Development**
**(Source: Colpier and Cornland (2002); adapted from Boston Consulting Group, 1972).**

- learning effects vary considerably between different technology systems within a field (e.g. wave and tidal energy, first and second generation biomass), and across the components making up the system (e.g. power modules, balance-of-plant, fuel supply chains, etc.) (see Figure 3, below).

[4] The need for more complex representations of innovation processes, especially learning-by-research as well as learning-by-doing, has led to the development of ‘two-factor’ learning rates in recent studies (e.g. Köhler et al., 2006). While these promise more realistic representations of early-stage innovation (where learning-by-research may be expected to dominate), they bring added data demands.

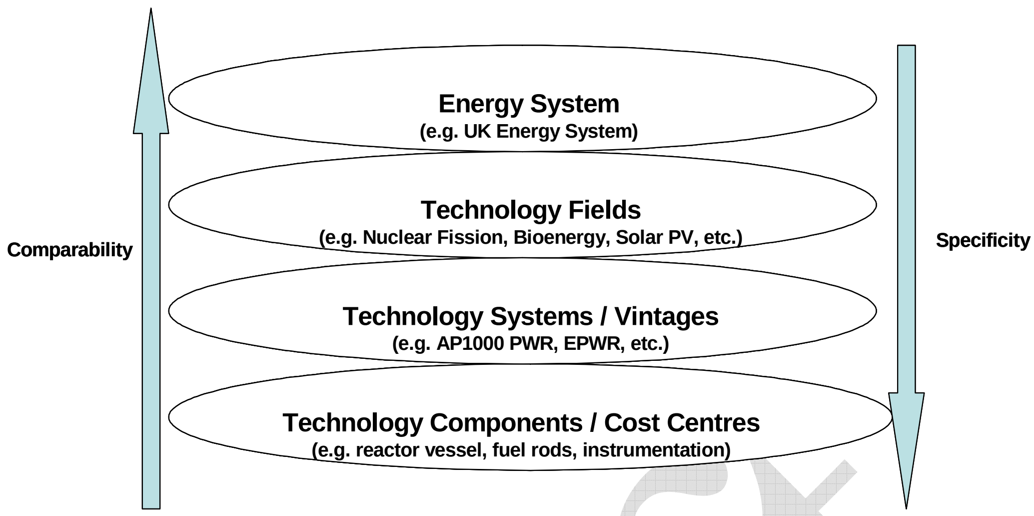


**Figure 3: Hierarchies in Learning Systems**

While these temporal, place and content sensitivities are 'ironed out' (and therefore essentially ignorable) over long-run global studies, they may well affect innovation outcomes at any level of detail at the national, organisational, and research programme level.

- Finally, because the outputs of long-term modelling exercises are highly sensitive to input data, seemingly minor differences in empirical learning rates derived from different studies have dramatic impacts on required learning investments and timescales for commercial breakthrough of individual technologies, and, at the system level, optimal energy mixes.

Despite these limitations, learning curves and learning rates remain a useful (and commonly adopted) tool for incorporating learning effects into energy system modelling, and their improvement and refinement has become a highly active research area in recent years. At the same time, their drawbacks suggest a research need to supplement quantitative, aggregated analyses with other tools which, while also simplifying to allow for comparison, retain greater technology-specific complexity.

## 3. Learning effects and learning systems

### 3.1 Technology-specific learning effects

Section 2 suggested that our tools for comparing emerging technologies need adequate ways of capturing and representing diversity. As a starting point for such an approach, technology-specific descriptive accounts of learning effects for several emerging power supply technologies were developed by members of UKERC's Learning Effects Working Group.[5] These accounts characterise learning effects for different technologies, and provide a basis for identifying points of commonality and disparity. The following are bulleted summaries of the accounts.

[5] Individual contributors here are: Bioenergy: Sophie Jablonski (Imperial College); Solar PV: Chiara Candelise (Imperial College), Marine Energy: Henry Jeffrey (Edinburgh University); Nuclear Fission: Paul Howarth (Manchester University); Nuclear Fusion: David Ward (UKAEA Culham); Carbon Capture and Storage: Nils Markusson (Edinburgh University).

### Bioenergy

- Bioenergy production systems are diverse and complex. The development of empirical bioenergy learning curves is difficult, given the variety of fuel types, plant scales and layouts, multiple outputs (electricity, heat, transport fuels, materials), and location-sensitive cost and performance. Fuel costs are a significant proportion of overall system costs. Analogies with fossil fuel plants are possible in some cases.
- Compared to more modular technologies (such as windpower or solar PV), significant learning-by-doing occurs during plant operation and maintenance. There has been relatively little research analysis of bioenergy learning effects, and published studies have tended to focus on a few large scale plants. One study of three plants (biomass CHP, fluidised bed boilers, biogas plants) suggested a 10% learning rate (Junginger et al., 2006).
- Different learning processes dominate for technologies developed on a local or regional scale (where learning-by-using and learning-by-interacting dominate), and technologies developed globally (where local dissemination of global knowledge becomes important).
- Cost reduction is not guaranteed: one study observed an increase of district heating plant costs, associated with a lack of monitoring of plant performance.

### Solar PV

- The solar PV system comprises ‘power modules’ (solar cells) and ‘balance of systems’ (BoS) components. PV modules represent around 70% of total system cost, and dominate learning analysis of PV.
- There has been considerable learning curve analysis of conventional crystalline Silicon (c-Si) modules, much less on thin film cells, almost nothing on third generation technologies (e.g. organic solar cells). This coverage reflects the availability of historic data, rather than future market potential.
- For pre-market technologies, expert elicitation techniques are used for estimating the impact of step-change breakthroughs. These may be subjective.
- There are very few studies of BoS costs, and these are highly varied e.g. grid-connected, off-grid, and regional differences in design and installation techniques.
- For conventional c-Si, learning priorities include: cell and module efficiencies, cheaper feedstock production, reducing material wasted, economies of scale, production process automation and product standardization.
- For thin film technologies, learning is focussed on cell efficiency, productivity (by developing large scale continuous in-line production), and developing flexible substrates to reduce installation costs.

### Marine Energy

- Learning is spread over a wide variety of concepts and components, and at the highest level, wave and tidal flow have different innovation needs. At the same time, some generic technologies and components offer opportunities for ‘shared’ learning (e.g. materials, moorings, resource assessment).
- There is limited operational data on prototype performance, and empirical evidence of learning and cost reduction. Development activity is tending to

focus on a few large-scale prototypes, up to around 1MW, which offer limited device iterations and learning opportunities.

- Across the wider R&D community, there is an emphasis on *learning-by-research*, given limited learning-by-doing opportunities. Additionally, an emphasis on conventional designs / components, rather than more radical options, possibly restricting step-changes in costs.
- The transfer of learning-by-doing within the 'developer community' is limited by commercial competition. These features may restrict opportunities for learning and cost-reduction.
- Learning priorities include:
    - Knowledge transfer from other sectors, e.g. offshore industry supply chains, and understanding the costs of transferring components to marine environment.
    - Identifying opportunities for collaboration with other industries and supply chain partners on potential 'step-change' technologies.
    - Greater understanding of O&M costs, given very limited experience in real operating conditions.
    - At an appropriate stage of development, design consensus to catalyse cost reduction, and 'designing-out' expensive concepts and components.

<u>Nuclear Fission</u>

- Nuclear power has a poor historic track-record of cost reductions with deployment, associated with non-standard plant and high construction costs, lack of financial scrutiny, complexity of safety systems and high costs of regulatory compliance.
- At the same time, there is some evidence of learning with deployment, for example, the incorporation passive safe features in more recent reactor designs.
- Future nuclear plant build is likely to involve private sector developers deploying standard global designs with little modification, and seeking fleet build so as to cover 'first-of-a-kind' costs. Where possible, systems will be built around standard international engineering components, rather than national supply chains
- Key learning priorities:
    - Within a generation, 'fleet build' cost savings in capital and O&M costs (there is some international evidence here drawn from Japan, Korea, France).
    - Between generations, estimating cost reductions associated with projected shifts from Gen II into Gen III and Gen IV systems.

<u>Nuclear Fusion</u>

- Fusion energy innovation involves the development of one-off experimental prototype designs. The system is highly co-ordinated internationally, and over time.
- At the system level, costing issues relate to estimating how costs are expected to change from one-off experimental systems, to *first-of-a-kind* commercial devices, and, eventually, multiple units.

- At the component level, prototype fusion systems may be separated into novel and conventional components. Conventional components are estimated to make up around 30% of overall system costs. To estimate an overall system learning rate, a single rate is used for all novel items, typically 15%. A zero learning rate is assumed for conventional components, giving an overall system learning rate of 10%.
- Industrial analogues are used for estimating learning rates where possible. For example, learning rates for superconducting magnet are estimated by analysis of magnets used in MRI scanners.

Carbon Capture and Storage

- A CCS technology system consists of three main components: *capture* of carbon dioxide from large point sources, mainly power stations; *transport* of $CO_2$ to a suitable storage location; *storage* of the gas, including injection, monitoring, and remediation.
- There is a very small learning rates literature on CCS. This focuses mainly on capture, which is expected to be the dominant cost component of the system.
- CCS is an assembly of components and technologies from other applications and sectors. Transport, injection, etc., draws on experience from the oil and gas industry. Capture draws on the chemical processing industry as well as fossil-fuelled power generation technologies, but it is also highly relevant to learn from previous emissions control technologies.
- The transfer of these technologies to the CCS system involves, for example, the scaling-up of capture technology, and the integration of capture and power generation plants. The integration of CCS with the power plant system poses technical as well as economic and regulatory challenges. A business model to drive the CCS value chain is needed.
- The technology is large scale, in terms of large capital investments, onto large point sources, possibly integrated into large pipeline network infrastructures. This scale creates a threshold for early investment, even though the technology is associated with large companies.
- The technology is generally considered ready for demonstration of the first full-scale, complete CCS system.

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### 2.2 Learning Matrices and Stages of Development

Alongside the briefing notes on learning effects and learning priorities summarised above, members of the LEWG also provided additional information in diagrams and tables. This took two forms:

a. For diverse technological fields (such as bioenergy and PV), different systems or configurations were mapped onto a 'stages of development' (or 'innovation chain') table.
b. For specific systems within a field, a component analysis matrix was used to differentiate between:
    - *Conventional components*, for which limited future learning opportunities may be anticipated (and a zero-level learning rate is often assumed).
    - *'Novel and specific' components*, for which learning processes are limited to within the system.
    - *'Novel and wider application components'*, which enable transfer of knowledge and components from other sectors.

Given space restrictions here, only a few examples of portions of the 'stages-of-development' and component analyses are provided in Appendix 1.

## 3. Comparing Energy Technology Innovation Systems: a 'learning pathways' model

### 3.1 Characterising Learning Systems: Generic Issues

Any effort at comparing different energy supply technologies must recognise stark divergencies in the development history, present status and future vision of 'rival' technologies. Technologies which are commonly grouped together in assessments of low carbon energy system have obvious technical, economic, organisational and political differences. For example, some technologies have demonstration or early commercial devices already in-place, while others are not expected to become available until the middle of the century at the earliest.

Despite these differences, a comparative reading of the expert summaries described in Section 2 and Appendix 1 reveal a number of common themes. These reflect underlying shared concerns, opportunities and barriers in the learning processes for different technologies. These common issues include:

1. *Design consensus or design variety:* some technology fields (e.g. nuclear fusion), have high degrees of technical design consensus (and also institutional co-ordination and concentration), while others (e.g. bioenergy, marine energy) span a wide variety of system designs and configurations, and also tend to be much more institutionally diverse, fragmented or even competitive. To some

extent, this relates to the stage of development of the technology, with more well-developed fields expected to have established a high degree of design consensus, and to exhibit less institutional diversity.

2. An emphasis on either relatively *incremental* progression of systems and components, or on more *radical* step-changes within a field, at the system or component level. Some fields (e.g. nuclear fission) are characterised by a relatively incremental progressions between system vintages over time, while for some other fields (e.g. marine, PV) there is greater emphasis on capturing step-change reductions in cost from developing and deploying radical systems or components.

3. Associated with radicalness or incrementalism, are differences in the *learning styles* being prioritised, in terms of the emphasis on *learning by research* (through dedicated R&D efforts) or *learning by doing* (through demonstration programmes and deployment of early designs). This also relates to an emphasis on either *dedicated learning* within a technology field, or *learning by adaption* of components developed in other fields, or *knowledge transfer* from more mature technologies.

4. *Scale effects*: scale and learning are closely intertwined: for example, a large number of small-scale prototypes offer, in general, greater ‘learning opportunities’ than fewer larger-scale devices (Neij, 2008), and also provide greater opportunities for upscaling as part of future cost reductions.

5. *Capital Intensity and Modularity* of technology systems: emphasis here varies between priority on reducing capital cost components (e.g. marine devices, PV modules or running/operating costs (e.g. for some bioenergy systems), and also of the *modularity* versus more *bespoke* systems. Modular systems in general offer greater opportunities for learning, although *fleet build* of large plant may also provide significant opportunities for learning by doing.

6. *Geographic aspects*: technology systems can be characterised by having relatively *globalised* or relatively *localised* learning systems (and also location-dependent or location-independent performance and impacts). Geographic dimensions also include perceived *market potentials*: for some fields, innovation activity and investments may be predicated on capturing mainstream market share, while for other fields, niche / local applications may be important, especially for initial deployments.

7. *Policy mechanisms, institutional/organisational interests, and funding arrangements*: The perceived market potential of emerging technologies also relates closely to their ability to attract and mobilise economic, organisational and political resources. In particular, the relative contributions of *public and private finance*, and the relative role here of ‘technology push’ or ‘market-pull’ mechanisms have powerful impacts on the dynamics and styles of learning pursued.

### 3.2 Two-parameter modelling

In seeking to develop a comparative framework within which to consider these themes, a first step was to position them on a spectrum according to the degree to which they appear to emphasise more fundamentally *technical issues* on one hand, to more fluid *social issues* (economic, institutional, and organisational) on the other hand (Figure 4, below).[6]

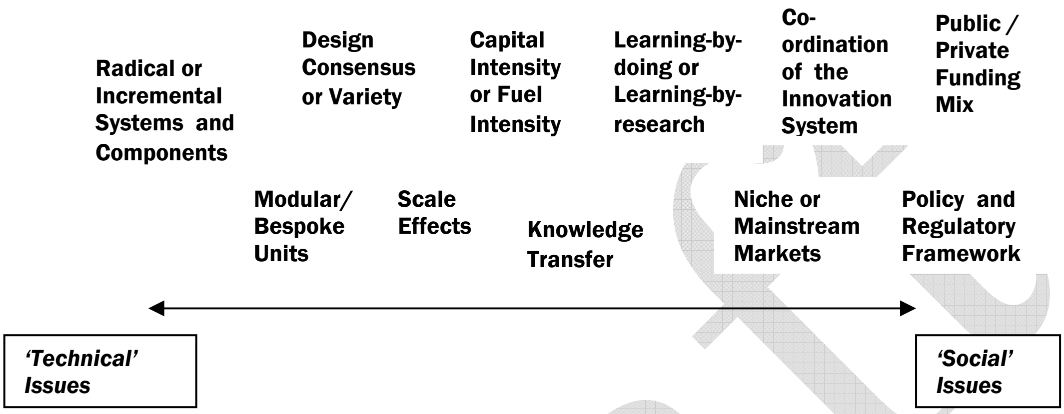


**Figure 4: Generic socio-technical issues in learning systems characterisation**

To enable comparison between different fields, a condensed representation of the themes and issues described above was needed. In this effort, predominantly 'technical' and predominantly 'social' issues were grouped together under two headings: an incremental-radical parameter (which is able to absorb many of the more technical issues described above), and secondly, a concentrated / distributed parameter (which captures many of the more social or institutional issues described above). These two parameters are understood as representations of distinctive (though not wholly independent) socio-technical aspects of learning, as represented in Figure 5, below.

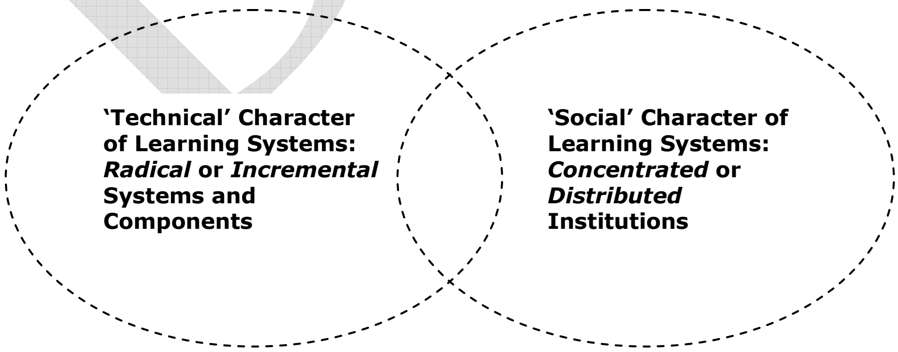


**Figure 5: Condensed Parameters for Learning System Analysis**

[6] It is important to note that there is no real division here, and what might be considered more rigid technical matters, such as prototype design, are clearly shaped by more 'fluid' social issues, such as available financial and political resources

Given that they appear to capture distinctive qualities of learning effects, these two parameters were then displayed as x and y axes to form the Learning Pathways Matrix (figure 6, below).[7]

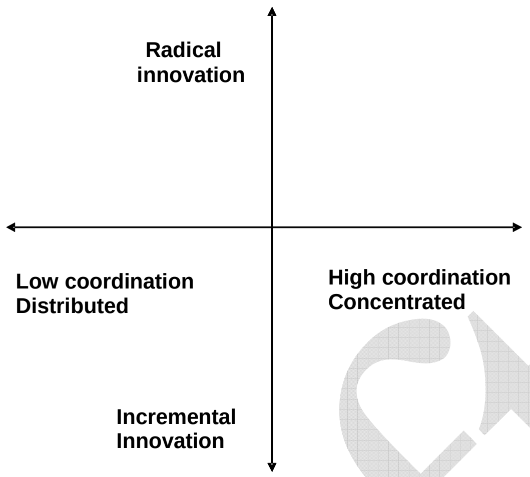


**Figure 6: Socio-technical Learning Pathways Matrix**

### 3.3 Applying the Learning Pathways Matrix

This section outlines how the learning pathways (LP) matrix has enabled a preliminary cross-technology and inter-temporal comparison of learning effects associated with different energy supply technologies. In Figure 7, below, two contrasting technology fields are represented: marine energy: a relatively diverse field with multiple emerging prototype designs, spanning two distinctive sub-fields (wave and tidal flow energy); and nuclear fusion, a radical but much more highly co-ordinated field, with international R&D activity aligned around a much smaller number of design prototypes.

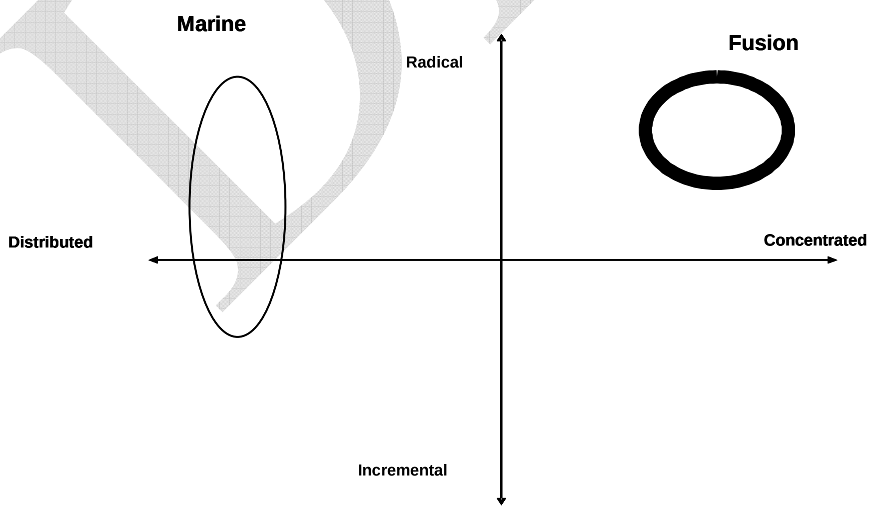


**Figure 7: Marine Energy and Fusion Energy Learning Fields**

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[7] This selection was also informed by wider analyses in innovation studies, and existing models of a similar kind applying to the governance of innovation systems In particular Smith et al.'s, (2005) 'typology of transition contexts'. Where Smith and colleagues focus on governance and institutions at the 'meso-level' regime, our interest here is rathermore with socio-technical processes in emerging niches, and on explicitly representing technical as well as social shaping.

As Figure 7 illustrates, a single technology field spans a range of innovation activity within its borders, and this range may be expected to be higher for more distributed (or less highly co-ordinated) fields.

Technology fields may incorporate both radical and more conventional/incremental systems (e.g. marine energy spans relatively conventional horizontal axis tidal flow technologies, and also more radical offshore wave capture prototypes). Typically, radical systems are less well-resourced, portrayed in the model as radical tails linking to incremental 'bodies', as shown in Figure 8, below.

The thickness of the border around the field is used to (roughly) indicate the levels of resourcing of innovation activity. The solid border indicates that flows of information and resources can pass relatively easily within a field. For example, more radical components and component configurations may be incorporated in successive generations of technology systems over time.

This was observed in the evolution of windpower technology: following the emergence of windpower as a modern supply technology in the 1970s, it has progressed from a weakly co-ordinated, low consensus and poorly resourced system (spanning a range of more or less radical designs), to become, today, a highly co-ordinated international industry, dominated by a few international manufacturers, and a clearly dominant design. The most successful innovation systems for windpower were characterised, initially, by a relatively incremental adoption of conventional components (drawn from other sectors, such as agricultural equipment); over time, these were able to incorporate more components from radical / ambitious programmes (Figure 8) (Garud and Karnöe, 2003).

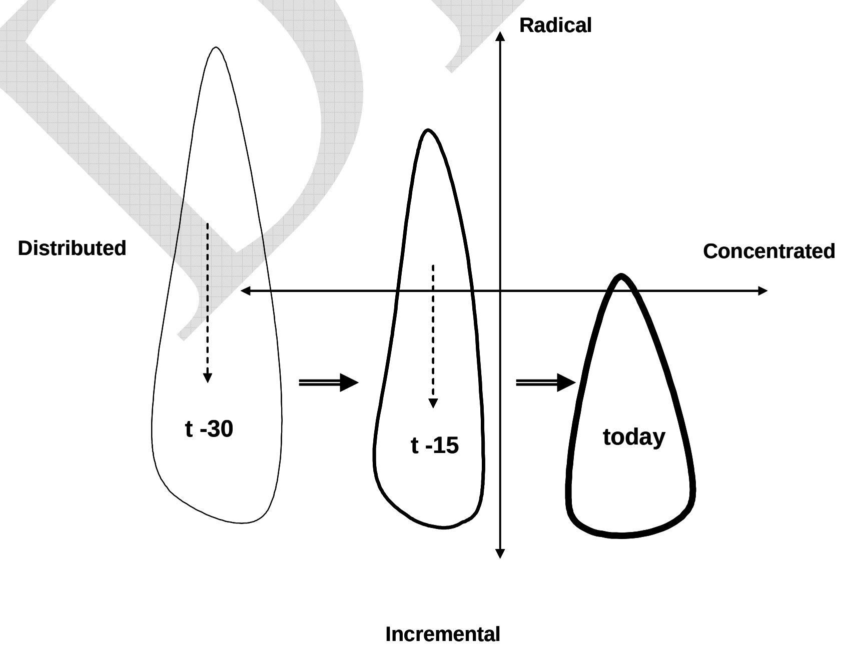


**Figure 8: Evolution of windpower learning field over time**

Reflecting their different origins and drivers, different technology fields show different development pathways over time. While windpower has developed via a predominantly incremental pathway, from a relatively weakly co-ordinated system initially dominated by small-scale developers, the Solar PV field, since its first emergence as a tightly co-ordinated technology associated with the NASA space programme, has, in the course of its commercialisation, diversified and become less tightly-co-ordinated. As shown in Figure 9, below, the PV field now spans a range of different applications and component configurations, from relatively incremental systems silicon-based power modules, to more radical thin-film and organic cells.

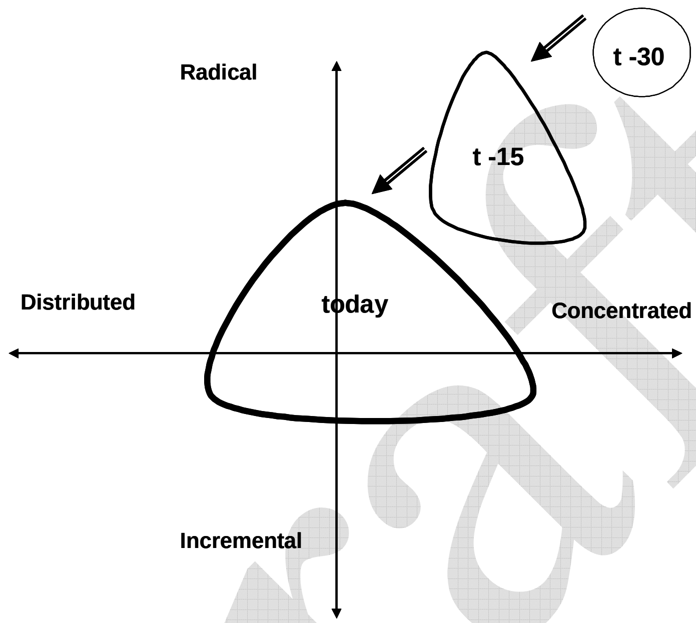


**Figure 9: Evolution of PV learning field over time**

The different quadrants of the learning matrix are associated with different entrepreneurial, financial, organisational and institutional interests. To a large extent, these interests govern the learning and innovation process for technology fields which reside in them. Different technological and financial risks are acceptable to the interests of the different quadrants, and as technology systems evolve over time, they attract different organisational and institutional interests. Figure 10 illustrates this, with stylised labels indicating the kinds of interests that dominate in each quadrant.

From our interest centralised electricity production,[8] Figure 10 also suggests that the goal for emerging supply technology systems – to become an established, commercial power generation technology – means migrating to the bottom right quadrant. This quadrant is characterised by a highly coordinated, concentrated and well-integrated system of centralised utilities and government institutions, and relatively incremental and low-risk innovations.

[8] Innovation and learning processes that may lead to, for example, a more decentralised generation system, are not represented here.

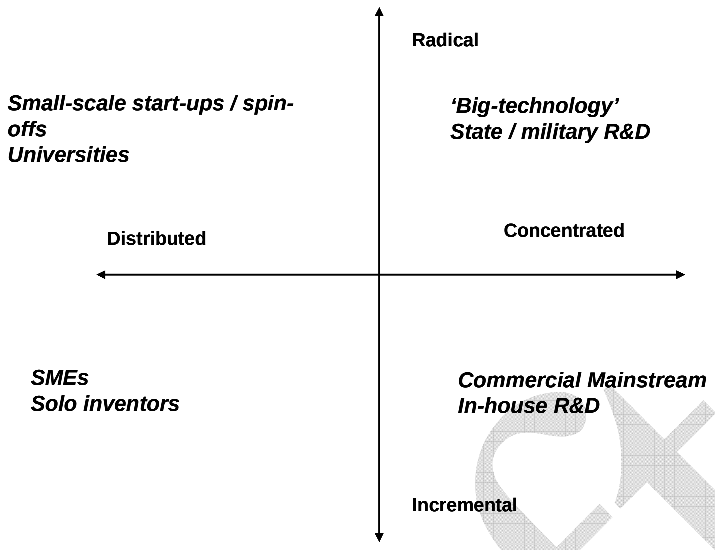


**Figure 10: Organisational Interests and Learning Quadrants**

There are different aspects to the opportunities and challenges for movement around the matrix. For example, the 'coordination challenge' of moving from the left hand side of the matrix to the right, and the 'technological challenge' involved in moving from top (radical) to bottom (incremental). As illustrated by Figures 7, 8 and 9 above, different emerging technological fields originate in different socio-technical contexts, and so prospective learning pathways will necessarily differ.

# 4. Conclusions

## 4.1 Summary and Discussion

This research is informed by the need for improved understanding of emerging energy supply technologies, and to find methods of analysis which, while facilitating system-wide comparison across technological fields, allow for the specifics and contingencies of technological learning systems. Established metrics for energy system analysis, such as learning curves and learning rates, although important and useful – and the subject of much ongoing research interest – have significant limitations here.

While the quantification of learning effects for modelling exercises inevitably involves simplification and generalisation, our basic premise is that qualitative analytical frameworks and case study evidence of technology-specific innovation systems, or wider sociotechnical systems accounts of sociotechnical change, can help inform and contextualise system modelling accounts.

The original research reported here was initiated by semi-standardised descriptions of the main learning effects for a range of technology fields, drawing on the expertise of members of the UKERC Learning Effects Working Group. Using these accounts, cross-technology analysis allowed for identification of generic themes (similarities and contrasts) across different technologies. In a further step of generalisation, two parameters were chosen to characterise learning systems – incremental-radical innovation and concentrated-distributed co-ordination – forming the 'learning pathways matrix'.

Together, these two parameters capture something of the sociotechnical complexity of learning effects. The coordination dimension serves to highlight important 'social' (organisational, institutional, economic, and policy) elements of technological learning, while the innovation dimension recognises important differences in the 'technical' character of change. The pathways matrix allows for incorporating research insights from the rich innovation studies literature on learning, such as terms of coordinating and linking actors together, and the distributed creation of variety in early-stage innovation (Jacobsson and Bergek, 2004, Jacobsson et al., 2004). The approach also recognises the structures and boundaries that shape learning within and across technological fields.

In relation to existing literature on technological transitions (Smith et al, 2005; Geels and Schot, 2007), the learning pathways approach highlights the diversity of niche origins of emerging technological fields.[9] Such differences imply different conditions for learning in early stage development, and different in becoming established. Different niche origins lead on to different learning pathways, with different governance and policy needs along the way.

This paper has set out a novel model of learning effects analysis that allows for greater complexity and specificity than aggregated quantifications such as learning rates, whilst still allowing for comparisons between technological fields. The learning pathways matrix highlights points of similarity and differences in the origins, status and prospects between emerging energy supply technologies – and the need to recognise these differences in policy and governance. It also allows for elaborations of the dynamics of technological fields over time, and of variety in terms of systems, components, and resource flows. As such, this cross-technology analysis has already provided useful insights.

## 4.2 Future Research

A number of themes from this research deserve further attention. Firstly, the issue of how different niche origins shape learning pathways, and the potentially ensuing regime transitions. The cross-technology analysis approach chosen here offers good scope for further work along those lines. Secondly, the policy implications of the pathways approach should be analysed further. The model appears to offer new ways of analysing which policies may be suitable for particular technologies. There may be scope here for identifying groups of technologies with similar pathways that can be targeted together, offering a middle ground between individual support, and generalised "technology-blind" policy.

Thirdly, it is worth considering opportunities for integrating learning pathways analysis with learning rates approaches. It is possible that more elaborate uses of learning rates are able to capture some of complexity of the pathways model. For example, the different pathways portrayed here could be illustrated with stylised

[9] There is a degree of arbitrariness here, since technologies have multiple "roots" starting points, there are significant differences in the sociotechnical character of emerging niches.

learning curves, and patterns of change (in terms of initial variety, later cost reductions, technology transfer and step changes) associated different 'ideal' pathways could be assembled.

## Bibliography


Bergek, A., S. Jacobsson, et al. (2008). "Analyzing the functional dynamics of technological innovation systems: A scheme of analysis." Research Policy 37(3): 407-429.

CEC (Commission of the European Communities) (2007). A European Strategic Energy Technology Plan (SET-Plan): Technology Map. Brussels, European Commission.

Colpier, U. C. and D. Cornland (2002). "The economics of the combined cycle gas turbine – an experience curve analysis." Energy Policy 30(4): 309-316.

DTI (2007). Meeting the Energy Challenge: A White Paper on Energy. London, UK Department of Trade and Industry.

Garud, R. and P. Karnoe (2003). "Bricolage versus breakthrough: distributed and embedded agency in technology entrepreneurship." Research Policy 32(2): 277-300.

Geels, F. W. (2004). "From sectoral systems of innovation to socio-technical systems: Insights about dynamics and change from sociology and institutional theory." Research Policy 33(6-7): 897-920.

Geels, F. W. and J. Schot (2007). "Typology of sociotechnical transition pathways." Research Policy 36(3): 399-417.

Grubb, M. (2006). Innovation analysis in theory and practice - A pragmatic and policy perspective. UKERC Workshop on innovation in energy systems: learning from economic, institutional and management approaches, Oxford, 22 March 2006.

Hekkert, M. P., R. A. A. Suurs, et al. (2007). "Functions of innovation systems: A new approach for analysing technological change." Technological Forecasting and Social Change 74(4): 413-432.

IEA/OECD (2006). Energy Technology Perspectives: Scenarios and Strategies to 2050. Paris, IEA.

IPCC (2005). IPCC Special Report: Carbon Dioxide Capture and Storage, Intergovernmental Panel on Climate Change.

Jacobsson, S., Björn A. Andersson, Lennart Bångens (2004). "Transforming the Energy System: the Evolution of the German Technological System for Solar Cells." Technology Analysis and Strategic Management 16(1): 3-30.

Jacobsson, S. and A. Bergek (2004). "Transforming the energy sector: the evolution of technological systems in renewable energy technology." Ind Corp Change 13(5): 815-849.

Jamasb, T. and J. Kőhler (2007). Learning Curves for Energy Technology: A Critical Assessment. Cambridge, Cambridge University Working Papers on Economics, CWPE 0752 & EPRG 0723.

Junginger, M., E. de Visser, et al. (2006). "Technological learning in bioenergy systems." Energy Policy 34(18): 4024-4041.

Kohler, J., M. Grubb, et al. (2006). "The Transition to Endogenous Technical Change in Climate-Economy Models: A Technical Overview to the Innovation Modeling Comparison Project." Energy Journal: 17-55.

Neij, L. (2008). "Cost development of future technologies for power generation--A study based on experience curves and complementary bottom-up assessments." Energy Policy In Press, Corrected Proof.

Neij, L., P. D. Andersen, et al. (2003). Experience Curves: A tool for energy policy analysis. Lund, Environmental and Energy Systems Studies, Lund University, Sweden.
Smith, A., A. Stirling, et al. (2005). "The governance of sustainable socio-technical transitions." Research Policy 34(10): 1491-1510.
Soderholm, P. and T. Sundqvist (2007). "Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies." Renewable Energy 32(15): 2559-2578.

# APPENDIX 1: Learning Matrices for Emerging Energy Supply Technologies

## Figure A1: Solar PV (Part)

| Technology component / sub-unit | Development Stage / Primary Learning Mechanism(s) | | | | |
|---|---|---|---|---|---|
| | R&D | Demonstration | Commercialization | Market accumulation | Diffusion/Fully commercial |
| Cell/module: crystalline silicon technology | | | Still supported, but good potential for quick cost reduction. Estimated 40% by 2010 | | |
| Cell/module: thin film technologies | | Smaller market share than c-Si. Good potential for increase in efficiencies and decrease in costs | | | |
| Thin film on flexible substrates | | | | | |
| Cell/module: other concepts technologies e.g. High efficiencies (III-V compounds), dye sensitized cells, organic cells) | Some pilot projects. In UK, university spin-offs | | | | |
| Concentrating PV | | | | | |

## Figure A2: Bioenergy (Part)

| Technology component / sub-unit | Development Stage / Primary Learning Mechanism(s) | | | | |
|---|---|---|---|---|---|
| | **R&D** | **Demonstration** | **Pre-Commercial** | **Supported Commercial** | **Fully Commercial** |
| Conversion (part) | | | | | |
| - Modern stoves and heat-only boilers | | | | | X |
| - Pressing and extraction for bio-oil | | | | | X |
| - Biomass cofiring (>50MW) | | | | X | X |
| - Gasification for power production in large units | | X | X | | |
| - Indirect firing for kW-scale power / CHP production using Stirling engine | X | X | | | |
| - Fast pyrolysis for bio-oil | X | X | | | |
| - Gasification as basis for hydrogen production (for fuel cells) | X | | | | |

## Figure A3: Nuclear Fission (Part)

| **Technology component / sub-unit** | **Component Characterisation** ***(assumed learning effects)*** | | |
|---|---|---|---|
| | **Conventional** ***limited / zero future learning*** | **Novel & specific** ***learning limited to the specific technology*** | **Novel & wider application** ***learning involves other sectors. Adoption in the specific technology may involve additional learning*** |
| **Reactor Internals and Vessel** | Limited opportunity for novel development. Conventional manufacturing technology based on heavy engineering (ship building etc) | | |
| **Steam Generators and Pressuriser** | Limited opportunity for novel development. Conventional manufacturing technology based on heavy engineering (ship building etc) | | |
| **Containment Vessel** | | Novel and Specific, passive safe systems alter containment vessel design and some future designs with inherent safety have no containment vessel. | |
| **Control & Instrumentation** | | | Some learning from outside the industry based on other industries (computer industry and application in oil, gas etc) |

## Figure A4: Wave Energy

| Main Topic | Component topic | Conventional no learning | Novel Specific | Novel Widespread |
|---|---|---|---|---|
| Device Structure | Ballast mass | X | | |
| | Device structure | X | | |
| Electrical | Generator | X | X | |
| | Controls | | | X |
| | Offshore power collection & transmission | X | X | X |
| Moorings | Anchors | X | | |
| | Mooring lines | | X | X |
| | Fittings/release mechanism | | X | |
| Mechanical | Power storage | | X | X |
| | Hydraulics | | X | X |
| | Turbine | | X | |
| | Seals | | | X |
| Control | Control system | | X | |
| | Instrumentation | | | X |
| Auxiliary | Assembly | | X | |
| | Insurance | | X | |
| | Project management | X | | |
| | Operation and maintenance | | X | |
| | Installation | X | X | X |

**Figure A5: Carbon Capture and Storage**
**(adapted from IPCC, 2005)**

| | **Capture** | | | **Transport** | | **Injection** | | | **System integration** |
|---|---|---|---|---|---|---|---|---|---|
| | **Post-combustion** | **Pre-combustion** | **Oxyfuel** | **Pipelines** | **Shipping** | **EOR (onshore)** | **Depleted oil and gas fields** | **Aquifers (on- and offshore)** | |
| **Mature market** | | | | X | | | | | |
| **Economically feasible under specific conditions** | X | X | | | X | X | X | | |
| **Demonstration** | | | X | | | | | X | |
| **Research** | | | | | | | | | X |

## Figure A6: Nuclear Fusion (Part)

| Technology component / sub-unit | Component Characterisation *(assumed learning effects)* | | |
|---|---|---|---|
| | **Conventional**<br><br>*limited / zero future learning* | **Novel & specific**<br><br>*learning limited to the specific technology* | **Novel & wider application**<br><br>*learning involves other sectors. Adoption in the specific technology may involve additional learning* |
| **Superconducting magnets** | | | X |
| **Buildings** | X | | |
| **Vacuum Vessel** | | X | |
| **Blanket/Shield/First wall** | | X | |
| **Heating systems** | | X | |
| **Turbine plant** | X | | |
| **Heat Transport** | | | X |