I. ABSTRACT

The paper discusses the use of experience curves in technology foresight and other prospective technology assessment. Focus is set on experience curves as a forecast instrument, considering the pros and cons when selecting this method. Consequences following the characteristics of the data material are discussed, in particular, period of time, availability of data, technological lifecycle, and the general learning environment in industrial and national systems of innovation.

Theoretically, the paper draws on innovation theory, technology sociology and on recent contributions to the science sociology.

The paper is based on empirical evidence covering almost half of all wind turbines produced globally over the last two decades.

The key result of this paper is a list of characteristics of the data input to experience curves that has to be analysed before one can use experience curves in prospective studies. Furthermore, the paper discusses the possible linkages between experience curve analyses and prospective methodologies.

II. INTRODUCTION

The experience curve describes how cost reductions appear in line with accumulated production. Accumulated production is used as a substitute for accumulated experience in the learning system. The mathematical expression of the experience curve can be written in the following way:

\[ C_t = C_0 \cdot \hat{Q}_t^{-k} \quad t = 1, \ldots, T \]

where observations of \( C_t \) is calculated as average over the observed variables. \( C_0 \) is the cost of the first unit produced. \( \hat{Q}_t \) is the accumulated production at time \( t \), and, finally, \( k \) is the learning rate. This expression states that for each time the production is doubled the relative cost reduction is given by \((1-2^{-k})\).

The concept of experience curves is based on learning curves first introduced by T. P. Wright reporting on a study of cost reductions in airplane production in America in the 1920’s and 1930’s (Wright, T. P., 1936). Note that the experience curve differs from the learning curve that describes the observed reduction in the number of required direct labour hours as workers learn their jobs. The experience curve by contrast applies not only to labour-intensive situations, but also to process oriented ones. The consultancy Boston Consulting Group (BCG) introduced experience curves in marketing strategy during the 1970’s. In both cases, experience curve studies were affiliated with manufacturing industrial products (Boston Consulting Group, 1972). This business
approach to experience and learning curves is still included in contemporary technology and strategy management literature (Grant, 1998; Miller and Morris, 1999; Johnson & Scholes, 2002).

During the 1990’s, experience curve analyses has attracted renewed interest for energy technology policy studies, and several projects on these issues have been carried out on this issue in Japan, Europe and America. Several models have been established that combines econometric models for cost of energy with industrial and technological dynamics. MARKAL is such a model (Seebregts et al, 2000). To that end, experience curves for new energy technologies is a useful tool to describing industrial learning, and a variety of studies of experience curves for energy technologies have recently been published (Neij, 1997; Rogner, 1998; Grübler et al. 1999; Wene, 2000; McDonald & Schrattenholzer, 2001; Colpier & Cornland, 2002; Neij et al., 2003; Neij, Dannemand Andersen, Durstewitz, 2004).

The reason for this renewed interest is that if global warming due to greenhouse gas emissions is to be mitigated, new energy technologies must be developed and utilised. These new technologies are not yet commercially competitive with established ones (fossil based) or might even not yet have been demonstrated in pilot plants. To develop and deploy these new technologies, governments have to take an active role in supporting R&D in new technologies and subsidising their early deployment. Hence, governments have an interest in assessing the long-term potential of new technologies as well as assessing the governmental expenditures needed for R&D and investment incentives. The timeframe for these assessments can be as long as 50 to 100 years.

Transferring experience curve analyses of historical data to prospective studies must be made very carefully. Development of technologies is affected by several factors such as policy initiatives, market developments, and learning within the industry. A simplified expression describing this development in the form of cost reduction as a result of accumulated experience is increasingly being incorporated in models to assess long-term development of energy technologies. Some of these applications use learning rates in order to predict future costs of the respective technologies and thereby the potential of renewable energy technologies in comparison with conventional energy technologies.

**VIII. EXPERIENCE CURVES AND PROSPECTIVE APPROACHES**

A number of studies have been carried out within the European Union on methodologies and approaches for assessing and designing policies in science and technology (i.e. Kuhlmann et al., 1999; Holtmannspötter and Zweck, 2001). Such reviews of methodologies for science and technology policy planning often discuss four distinct groups of approaches: Science and technology foresight, technology forecasting, technology assessment and science and technology policy evaluation.

Science and technology foresight has been defined as: "the process involved in systematically attempting to look into the longer-term future of science, technology, the economy and society with the aim of identifying the areas of strategic research and the emerging generic technologies likely to yield the greatest economical and social benefits", (Martin, 1995). Other definitions can be found in other references, but there is a general consensus that foresight is concerned with the impact of technological

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17 This paragraph is elaborated from paragraph 1.2.3 in Neij et al. (2003).
development on society, with the focus on the identification of broad future trends and socio-economical aspects of emerging technologies. A broad cross-societal dialogue is the most central trait of foresight exercises. Here, experience curve studies may play a limited role as foresight exercises often take a very broad approach and utilise several methodologies.

**Technology forecasting** is also concerned with emerging technologies and their implications, but compared with science and technology foresight, it involves less (or no) dialogue between the stakeholders. Where foresight is often associated with public policy forecast, it is often associated with business strategy. A definition of forecast in such a business perspective is: “.. systematic recognition and observation of new technologies (‘weak signals’) or existing technologies, the evaluation of their potential and their importance for the competitiveness of the company, and the storing and diffusion of information.” (Reger, 2001). Technology Forecasting primarily focuses on technological and economical aspects. Here, experience curve studies can play an interesting role in forecasting or predicting the future. Techno-economical development is a central issue in the prospective use of experience curves. Technology forecasting is often mentioned together with technology surveillance or technology intelligence approaches, such as monitoring, early warning, or technology radar.

**Technology assessment**, as Science and Technology Foresight, deals with the impact of new and emerging technologies on society, and cross-societal dialogue is essential. Technology assessment in governmental policymaking has especially played an important role in Denmark, and the Danish Board of Technology has established international recognition for its activities. Technology assessment tends to focus on the risks of technologies and secondary implications for society, and the examination of norms and values is important. Consequently, it seems that experience curve analysis cannot play an important role.

In several European countries, and especially in Scandinavia, an “evaluation culture” has been developed in science and technology policy planning. **Science and technology policy evaluation** approaches vary from country to country and from issue to issue. A central issue in policy evaluation is the impact of the policy in question. Here, historical experience curve analysis for the technology in question is a relevant tool, provided that reliable data is available. This will be discussed in more detail later in this paper.
Table 1 gives an overview of the role of experience curve studies in the different approaches used in the science and technology policy planning discussed above.

In general, experience curves can be considered a complementary tool for other prospective methodologies. As it is often not possible to directly foresee changes in technology or markets by the extrapolation of experience curves, it is necessary to combine experience curve studies with other prospective methodologies for analysing the future, such as scenarios or Delphi studies.

In addition, it might be of interest to analyse expectations regarding the future development of science, technology and markets when making decisions in research policy. A small group of European social scientists has over the recent 5 to 8 years studied expectations in science and technology (van Lente & Rip, 1998; Selin, 2002).

<table>
<thead>
<tr>
<th>Approach</th>
<th>Role of Experience Curve Studies</th>
<th>Disadvantage(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Science and Technology Foresight</td>
<td>Not an obvious tool, since societal dialogue is the essential feature.</td>
<td>N. A.</td>
</tr>
<tr>
<td>Technology Forecast</td>
<td>One important tool, together with other trend extrapolation methodologies such as regression analysis and s-curve analysis.</td>
<td>Reliable technological data is seldom available. Can only be used for a series of incremental changes. Major shifts in technology cannot be predicted. Must be combined with scenarios or Delphi techniques.</td>
</tr>
<tr>
<td>Technology Assessment</td>
<td>Not an obvious tool since societal dialogue and assessments of the consequences of new technologies are essential.</td>
<td>N.A.</td>
</tr>
<tr>
<td>Science and Technology Policy Evaluation</td>
<td>One among several tools for analysing the impact of S&amp;T policies in a historical perspective.</td>
<td>Reliable technological data is seldom available. Must be combined with interviews, case studies, etc.</td>
</tr>
</tbody>
</table>

**IX. EMPIRICAL DATA**

The data used in this article includes data for Danish turbines produced and installed in Denmark from 1981 until 2000. A total of 6,424 electricity-producing wind turbines have been installed in Denmark until year 2000. Of these, 3,226 turbines were included in this project, which is equivalent to 50% of the turbines installed in Denmark. Amongst the manufacturers in this data set, we find Bonus, Kuriant, Micon, Nordtank, Vestas, Windworld, and NEG Micon. The data used for analysing the development of wind turbines include information on year of installation, manufacturer, turbine type, rated power (kW), rotor diameter (m), hub height (m), annual production at a reference site (ref. wind speed (m/s), ref. height (m)), number of installed units, turbine prices, cost of foundation, etc.

The data have been collected from two main sources. Technical data and the number of turbines were obtained from the company Energi- og Miljødata (EMD) in Aalborg, Denmark. EMD collected data until 2001 on behalf of the Danish Wind Turbine Owners’ Association with a grant from the Danish Energy Agency. This data has been
combined with list prices from different sources. The Danish Energy Agency has over
the years financed information on list prices of wind turbines from Danish wind turbine
manufacturers. From the late 1970’s until the mid 80’s, the Test Station collected data
for wind turbines at Risø National Laboratory. Between the mid 80’s and the late 90’s,
the Danish Technological Institute collated data, and in recent years, data has been
collated by EMD in Aalborg. Information on list prices for foundations, grid connection,
insurance, etc., has been included in recent years.

With the use of an annual statistical report issued by the company BTM-Consult, we
were able to estimate the total production of a number of companies from 1989 to 2000.
Based on our knowledge on domestic sales from the above-mentioned source, we were
able to estimate the exports over the period 1989-2000. In order to see more about
validity and description of the data, see (Neij, L. and others, 2003).

The focus of the experience curve is mainly on cost development with increased
production. Figure 1 is an example of an estimated experience curve with data where
costs per unit of production (Euro/kWh/year) are expressed as a function of
accumulated installed capacity (kW). Methodology to estimate this cost of electricity
can be found in Redlinger, Dannemand Andersen and Morthorst 2002. The equation for
the experience curve can be expressed as follows with a rather good fit of 86% of the
variance described by the model:

\[ C_t = 1.78 \cdot \hat{Q}_t^{-0.19}, \quad t = 1981, \ldots, 2000 \quad (R^2 = 0.86) \]  

Figure 1. Estimation of an experience curve for Danish wind turbines in 1981-2000 (log-log scale).

X. FORECASTING WITH EXPERIENCE CURVES

The experience curve has a good explanation factor \((R^2)\) and is, therefore, obvious to
use as a model to describe technological development of renewable energy technologies.
But, it is important to remember that the relationship between costs and cumulative
capacity is a historical relationship, whereby, for example, predictions must be made with cautiousness.

In order to evaluate the possibility of using the model to predict future development, we now examine the errors created using the experience curves for prediction by the use of an example with the Danish wind power data. We look at an example of prediction using data from the period 1981-2000. In three different time steps (1985, 1988, and 1994), we try to predict the unit cost at an accumulated capacity at 2600 MW, which corresponds to the observed accumulated capacity in 1995 (
Table 1 and The test involves estimation of three experience curves on the basis of 5, 8, and 14 observations, respectively. With the first curve, we are standing at the end of year 1985, with the information from the period 1981-1985, trying to predict the costs with an accumulated capacity of 2600 MW. The result of this prediction is then our expectation for the year 1985 to the cost with an accumulated capacity of 2600 MW (Figure 2). **With the second curve**, we obtain the prediction in Figure 3, and the third in Figure 4.

Figure 2). The points (■) illustrate the observations that are used in the calculation of the predictions, and the points (x) illustrate the observations observed after the calculation is made.

The test involves estimation of three experience curves on the basis of 5, 8, and 14 observations, respectively. With the first curve, we are standing at the end of year 1985, with the information from the period 1981-1985, trying to predict the costs with an accumulated capacity of 2600 MW. The result of this prediction is then our expectation for the year 1985 to the cost with an accumulated capacity of 2600 MW (Figure 2). With the second curve, we obtain the prediction in Figure 3, and the third in Figure 4.

**Figure 2. Prediction of the cost level for wind power in 1995 with the use of 5 observations.**

![Figure 2](image1)

**Figure 3. Prediction of the cost level for wind power in 1995 with the use of 8 observations.**

![Figure 3](image2)
This way, we end up with three predictions and three prediction intervals, which indicate the development in predictability as more information is gained. The method for the estimation of the predictions and prediction intervals can be viewed further in (Jensen, 2004a).

The actual observation in 1995 lies at 0.37 Euro/kWh, and this value actually lies outside the prediction interval with 5 observations. In the next interval, it lies at the bottom of the interval. This is also illustrated by the fact that the prediction is higher than the actual observation in all five cases.

**Figure 4. Prediction of the cost level for wind power in 1995 with the use of 14 observations.**
Table 1. Difference in estimated parameters (constant, experience parameter, and prediction interval) depending on the amount of information present at the time of estimation. Examples are shown for the years 1985, 1988, and 1994 ($\varepsilon =0.05$).

<table>
<thead>
<tr>
<th>Prediction Intervals</th>
<th>Obs.</th>
<th>Constant</th>
<th>Experience Parameter</th>
<th>Prediction</th>
<th>Lower Prediction Interval</th>
<th>Upper Prediction Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981-1985</td>
<td>5</td>
<td>1.03</td>
<td>-0.04</td>
<td>0.76</td>
<td>0.37</td>
<td>1.54</td>
</tr>
<tr>
<td>1981-1988</td>
<td>8</td>
<td>1.33</td>
<td>-0.12</td>
<td>0.53</td>
<td>0.27</td>
<td>1.03</td>
</tr>
<tr>
<td>1981-1994</td>
<td>14</td>
<td>1.62</td>
<td>-0.17</td>
<td>0.42</td>
<td>0.24</td>
<td>0.74</td>
</tr>
</tbody>
</table>

The change in prediction interval for the experience curve indicates the effect on the uncertainty in the predictions of adding information each year.
Table 1 also shows an example, where we try to predict the unit cost for 10 years ahead with the amount of information gathered in 1985. The actual costs in 1995 are not included in the confidence interval of unit costs predicted in 1985. However, by the year 1988, the prediction is in the interval, but it is only relatively close to the actual value by year 1994.

These analyses indicate the problems of using the experience curve to predict future development within renewable energy technologies, as the amount of data is often relatively limited. Using the experience curves as prediction models, having only a few data points (in these cases 7-10 years), could give results far from the actual observations and, at the same time, we have no idea whether the prediction is optimistic or pessimistic. If the idea of the prediction were to evaluate future investments in renewable energy technologies, both by private and public investors, the uncertainty in the investment will not decrease when we use experience curves to predict future possibilities of the technology. Unfortunately, sufficient data is often not available at the time when we wish to predict future developments in renewable energy technologies. Furthermore, this type of model has presumptions of a future continuous development, which corresponds to the development so far. Often, this presumption is not quite entitled, when speaking of new, rather unknown renewable energy technologies, where “jumps” are more often to be observed.

8. Improving Forecasts with the Experience Curve

Addressing the problems of forecasting with other models and knowledge of data input, for example, with respect to the technological lifecycle.

The interest in quantitative models that are able to not only describe historical development, but also predict and not at least explain innovation processes are strong, increasing with increasing use of renewable energy technologies in power supply today. But before using the limited number of models, it is very important to discuss data input in the process of technology description in all types of quantitative models.

In the case where the technology is just emerging, and there is only data from the period of the technology lifecycle, there is often a large variance in the data (illustrated by the first dotted circle in Figure 5). A prediction at this time often results in a large estimate of the cost (Point a). In the case where there is no data from the first phase, and the technology is in the second phase, the prediction is lower than the actual values of the cost (Point b). The actual observation often lies in a place between these two points (Point c), and in order to reach it, it is preferable to have data from both the first and second phase of the technological lifecycle. Data from the first phase is not so important as the variance is high due to many concepts. This information can be used as a guideline to know whether the fitted values are over or under estimation.

Figure 5. Illustration of span between prediction possibilities depending on available data (X indicates actual observations) Source: Jensen, 2004b.
The description of how the technological lifecycle can affect the prediction of data can also be seen in the previous case of forecasting. In all three estimations, the prediction was above the actual observation, which is mainly caused by the observations at the beginning of the time interval. If an experience curve on the basis of data in the middle of the technological lifecycle is estimated, chosen here to be 1985-1991, we obtain the result in Figure 6.

As expected, the prediction lies below the actual observation, which causes an overestimation of the cost development, the result being that it is very important to have information of the data lying behind the estimated experience curve in order to know whether the predictions are cautious or optimistic.

Another way to improve predictions is to improve the model used. One example could be to include more explanatory variables in the predictions in order to, for example, avoid the restriction of total continuity in the data.

An example of another type of model could be including manufacturers and generations of the technology. For example, in a technology system, where we have $J$ generations of one technology type and $I$ manufacturers, the learning curve theory states that we can construct one experience curve for each production line, i.e., $JxI$ learning curves. The theory of the experience curve furthermore states that it is possible to add all these generation and manufacturer specific experience curves to one, by constructing averages for both manufacturer and generation (Figure 7).

Figure 6. Prediction of the cost level for wind power in 1995 with the use of observations from the second period (1985-1991).
Figure 7. Reduction from a manufacturer and generation specific experience curve to one general experience curve. Source: Jensen, 2004b.

A way to improve the prediction possibilities of the experience curve could be to include more information on either manufacturers and/or generations of the technology. Instead of making averages for both \( J \) and \( I \), we can also choose only one of them, wherefore, we calculate averages for, e.g., producers \( (I) \), and hence, end up with one experience curve for each of the generations (in total \( J \) curves). In this case, we get a model that represents product innovation with shifts in curves, and process innovation with continuous movement down a curve (Jensen, 2004b). Likewise, averages for generations \( (J) \) result in one experience curve for each producer (in total, \( I \) curves). In this case, we on the other hand get a model that states that learning only happens within an organisation with insignificant exchange of knowledge.

These types of analyses can be used to obtain knowledge of the learning processes within the area of a specific technology. If the data is more compatible to a model with generations, there is a large part of common knowledge within the technology area, whereas the other model represents extensive specific organisational knowledge.
Applying statistical analysis on wind power data (Jensen, 2004b) using information on both generations and manufacturers makes it possible to test the possibility to construct averages. The final results from the statistical analysis presents an analysis with the structure illustrated in Figure 8.

That is, one experience curve for each generation of the technology, but the experience rate is equal for all generations, i.e., equal slope for all curves (Figure 8). Therefore, the construction of the experience curves does not depend on information from individual producers. The interpretation of this could be that the information on the innovating system of wind power in Denmark is common knowledge, i.e., all producers have access to almost the same information.

Figure 8. Illustration of the model structure (Jensen, 2004b).

Following, technological development in the model can be described by starting with the first generation of the technology with the curve in the left-hand corner (Figure 8). Then, the process innovation brings us down this curve and reduces costs with the percentage indicated by the experience rate. When a new generation occurs, we have a period with the presence of two types at the same time, which both develop down their respective curves. Remember that the input to the experience curve is the total accumulated production, wherefore, points at vertical lines are all observed at the same point in time. Shifting to the new generation, i.e., jumping between two curves represents the product innovation.

In order to illustrate the prediction possibilities with this type of model, we have tried to predict future costs in the case of wind power. This is illustrated in
Figure 9 where observed points (●) and the fitted values (o) for each group of values (determined by type of machine or generator size). Variation in the vertical direction is caused by a shift in generation.
Figure 9. Observed (●) and fitted values (O) for the model illustrated in Figure 8.

It can be seen that the fitted values describe observed data very well, and there is no tendency to over or underestimate the development of large accumulated production, as the fitted values lie within the spectrum of the observed values. In a model with this kind of structure, one should be aware of the predicted limitations. The model is only designed to predict within the observed generations. That is, it is not possible to predict a new generation, as it was not part of the input data. This problem is, however, relatively easily solved, as we can use the last generation as approximation for the prediction. This way, we only construct a new generation when there is sufficient data to establish this. For a further comparison between this type of model and the traditional experience curve, see (Jensen, 2004b).

XI. EXPERIENCE CURVES COMBINED WITH OTHER PROSPECTIVE METHODOLOGIES

Above, we have discussed ways of improving forecasts based on extrapolation of the experience curve. In this paragraph, we will discuss combinations of experience curve and other prospective methodologies.

The key interest in using the experience curve in a prospective manner is the prediction of future cost reduction. The variables for this are (1) the prediction or anticipation regarding the slope of the experience curve and (2) the prediction of the cumulative production.

Innovation System Dynamics

As argued elsewhere, experience curve analyses must be accompanied by a description and understanding of the whole innovation system and of the roles of the many actors involved in that system (Dannemand Andersen, 2004). We will in the following paragraph draw on terms and considerations from the recent 20 to 30 years of innovation studies and by this try to elaborate on the implications for the prospective use of experience curves.
The original use of experience curves was based on analyses of incremental changes within a certain technological paradigm (technological trajectories) and improved manufacturing of identical components. The recent use of the concept of experience curves for energy technologies differs from this in the sense that focus has put technological innovation on a higher systemic level, such as the whole wind turbine industry and not at identical components. With a disciplinary basis in evolutionary economics and political science, one line of studies explicitly treats technological trajectories. A wider definition of the paradigm includes what could be called the wind power innovation system or the Danish wind turbine industry cluster. It is well documented in that, the case of the Danish wind turbine industry, technological innovation had taken place as series of incremental changes rather than few radical changes (Dannemand Andersen, 1993; Karnøe, 1995; Redlinger, Dannemand Andersen, Morthorst, 2002).

In order to look further into the black box of industrial innovations, we need a simple model wherein the sources for accumulated knowledge and experience are introduced. See figure 10. Central in the model are the three types of what knowledge is about in the industrial innovation process: Conceptual knowledge, processual knowledge and utilisation knowledge (Rosenberg 1982; Vincenti 1984). This corresponds to a product’s major lifecycle phases: design, manufacturing and use.

![Figure 10. Overview of sources of learning. Source: Dannemand Andersen, 2004.](image)

Experience-based knowledge is then created in three ways. Firstly, through the process of developing and designing a machine is carried out by use of the available knowledge. But new knowledge is also created through this process and this new knowledge is directly embodied into the design or redesign of the machine. This could be improved knowledge on using computer codes for design and stress calculations. Also, targeted research activities creating codified knowledge are used this way. However, we are not just talking about research, but about the learning processes creating tacit knowledge.

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18 Terms such as natural trajectories, technological imperatives, technological regimes, (Nelson & Winter, 1977), and technological trajectories (Dosi, 1988) are used to describe this from different approaches.


20 On the terms “embodied” and “disembodied” knowledge see Rosenberg (1982).
affiliated with development and design. Secondly, in the centre of the model is the type of learning Wright observed in the aircraft industry and the type of learning that the BCG deals with. Learning through manufacturing will lead to improved or cheaper manufacturing of the same product. The product will not be exposed to visible changes due to these improvements - we are talking about disembodied knowledge. In wind turbine technology, this could comprise better logistics in purchasing and distribution, outsourcing of production, improvement of the speed of welding robots, etc. Some of the experience with manufacturing might lead to suggestions for changes in the design of the manufactured product. This type of new knowledge will be embodied in the product as artefactual changes that will improve the manufacturability of the product. Thirdly, experience can be gained through the use of a product as suggested by Rosenberg (1982). Rosenberg primarily focussed on learning gained through the use of a machine and leading to an improved or more efficient use of a machine. This new knowledge is disembodied since it will not affect artefactual changes of the machine. But if the learning is linked to a feedback to the design of the machine, the new knowledge can be embodied therein.

The model could be added with an element concerning knowledge and learning on dismantling and recycling, but the purpose of this article does not make it necessary to include this type of learning.

It would be of great interest if we could describe and quantify each element of learning shown in figure 10. In practice, this is very difficult, partly due to the above-mentioned difficulty in measuring change in knowledge and partly due to the fact that measuring changes in technology requires long-term tracks of detailed statistical data that is considered highly confidential by industry. Nevertheless, the model gives us a tool for describing many of the elements and, as we shall see in the empirical part of this article, even quantifying some of the elements.

When analysing experience curves for a certain technology, it is important to understand how many of these three sources of learning are included in the analysis. If focus is put on cost reduction of components alone, the learning-by-using elements are not included at all. This is a common flaw in many recent experience curve studies of energy technologies.

**Mapping or Relevance Trees**

As indicated in an earlier paragraph in this paper, detailed knowledge on the technology and the innovation system in quest is important in order to improve the quality of forecasts based on experience curves. But, apart from this, the experience curve on system level can be decomposed in the specific elements of the technology. This will improve the policy or strategy advice made from the experience curve analysis. An example of such relevance tree is elaborated in Dannemand Andersen et al. (1996). Relevance trees are very useful when analysing the future slope of an experience curve, but they are less useful when determining the future cumulative production.

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21 On the terms “codified” and “tacit” knowledge see Vincenti 1984 or Nonaka & Takeuchi, 1995.
22 Rosenberg (1982) introduced the distinction between learning by doing and learning by using.
**Diffusion Modelling, S-Curves and Analogies**

The importance of understanding the role of the technology’s lifecycle phases is already emphasised in an earlier paragraph of this paper. Therefore, it is useful to check scenarios for the future diffusion of the technology with such traditional S-curves. The forecasts by BTM Consult mentioned above, tended in the 1990’s to underestimate the growth rates of the wind turbine market, whereas the latest forecast did overestimate the growth rate. The reason for this might be that the technology has reached a more mature lifecycle stage. This is very easily detected from viewing the market penetration curve for wind energy and comparing it with another energy producing technology (see figure 11).

**Figure 11. Comparison between diffusion of nuclear and wind power.**

**Scenarios**

Scenarios can be defined as stories describing different but equally plausible futures. They are developed using techniques that systematise the perceptions of alternative futures (Schwartz, 1984). Two types of scenarios can be made. The extrapolative or predictive type of scenario draws on elements from forecasted techniques. Normative scenarios often reflect more radical discontinuities and they can be combinations of technological possibilities and political ambitions or targets.

Within the line of descriptive scenarios, the most comprehensive study is the annual World Market Update and Forecast from the consultancy, BTM Consult (BTM Consult, 2003). These forecasts are based on manufacturers’ information and order stocks, existing national policies, programmes and targets, etc. Based on this, the 2003 issue forecasts the global market for wind power 2003-2007, and extrapolate this development to year 2012. Other descriptive scenarios have been published by the International Energy Agency (IEA, 2002). IEA has developed two scenarios; quite traditionally named, Reference Scenario and Alternative Policy Scenario. The World Energy Council has formulated two comprehensive predictive scenarios for the World’s 2020 energy supply - a Current Policy Scenario and an Ecologically Driven Scenario (WEC, 1993 and 1994). These scenarios also contain expectations for the cumulative installation of wind power.

Within the line of normative scenarios, several organisations and consultancies have formulated forecasts for future utilisation of wind power. The European Union's white paper on renewable energy has established an ambitious target for wind power in Europe of 40 GW by 2010. This can be perceived as a normative scenario, and policies from now on are being established in order to meet this target. Another normative scenario has been formulated by the non-governmental organisations, the European Wind Energy Association and Greenpeace (EWEA/Greenpeace, 2003). The study has analysed the possibilities for penetrating the World electricity systems with 12% of
electricity supplied from wind power plants - once in the next century. This study also utilises experience curves to estimate the future cost of wind power.

Scenario processes can also be used to facilitate expert group discussion on the future characteristics of the technology itself. This might ultimately lead to a conclusion on the future slope of the experience curve. Such technology scenarios can be combined with a relevance tree structure as a point of origin for the scenario building. See Dannemand Andersen and Bjerregaard (2001) for an example of this approach.

**Delphi Studies**

In practice, Delphi studies are based on questionnaires sent to a selected panel of experts. Such a study can cover from a narrow topic to a wide technological foresight exercise at national or supranational level. The foresight period may range from few years to twenty or thirty years. A Delphi process includes typically two rounds where the results from each round are communicated to the participants in order to achieve a consensus after the final round regarding the issue under investigation.

Technology foresight studies based on the Delphi method have been carried out on a national level in Japan since the 1970’s. In an earlier paper, three foresight studies using Delphi techniques were analysed (Dannemand Andersen, 1999). The three Delphi studies were: a Japanese (NISTEP, 1997), a German (Cuhls, Blind, Grupp, 1998) and a British (Loveridge, Georgiou, Nedeva, 1995). Some few hints on both cost of technology and cumulative production can be drawn from these national Delphi surveys, but, in general, we need to turn to more specialised Delphi surveys to gain useful information for an experience curve analysis. At least one Delphi-like survey has been carried out on wind energy (Dannemand Andersen & Bjerregaard, 2001). The conclusion is that Delphi studies can be very both when analysing the future slope of an experience curve and the future cumulative production.

**XII. CONCLUSIONS**

A traditional experience curve is simple and easy to understand, and can be estimated with sparse data. Some of the disadvantages with this model are the problem with no continuous data from, for example, jumps caused by generation shifts. Furthermore, predictions are very sensitive to time of data collection with under-estimation of costs with data from the period of a technology’s lifecycle and over-estimation with data from the second period phase only (Figure 5).

The second suggestion to improvement of forecasts using the experience curve was to expand the model with one more explanatory variable (generation). The level variable generator type changed the model with a level shift for each group of generators, but the learning rate was still constant for all generator types. The inclusion of generator resulted in a model considering the up-scaling effect. With respect to predictions with this type of model, it performs much better than the original experience curve (when including uncertainty). But one of the disadvantages is that for new generator types, there are no predictions, wherefore, one is forced to use the closest generator type. Additionally, there is a demand for data at generator level, which is not always easy to obtain.
However, all of the presented models lack in contribution to the understanding of underlying dynamics, for example, all models have a constant learning rate throughout the technological lifecycle. Experience curve based models should, therefore, mainly be used to historical description or as a prediction tool instrument in combination with other prospective methodologies.

Table 2. Some prospective methodologies’ linkages with experience curve analyses.

<table>
<thead>
<tr>
<th>Prospective Methodology</th>
<th>Used for Prediction or Anticipation the Slope of the Experience Curve</th>
<th>Used for Prediction of the Cumulative Production</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovation system dynamics</td>
<td>++</td>
<td>-</td>
</tr>
<tr>
<td>Mapping and relevance trees</td>
<td>++</td>
<td>-</td>
</tr>
<tr>
<td>Diffusion modelling, S-curves and analogies</td>
<td>++</td>
<td>++</td>
</tr>
<tr>
<td>Scenarios</td>
<td>+</td>
<td>++</td>
</tr>
<tr>
<td>Delphi studies</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

When used in prospective analyses, experience and learning curves belong to the family of trend extrapolation methodologies. The use of experience curves, and similar trend analysis tools, is usually suitable under conditions of low uncertainty, for series of incremental innovations, in short-term ranges, and on a highly aggregated level. On the other hand, trend analysis tools are seldom recommended for prospective analysis under conditions characterised by high uncertainty, shifts in technology or market situation and long-term ranges. We are then left with judgemental methodologies, such as interviewing experts, expert panels, Delphi surveys, etc. On the other hand, long-term projections of technologies are sometimes needed and a combination of experience curves analyses and judgemental methodologies might be the only available tool. In this paper, we have analysed some examples of such combinations.

XIII. REFERENCES

Boston Consulting Group (1972), Perspectives on Experience, Boston, MA


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Experience curves

\[ C_t = C_0 \cdot \hat{Q}_t^{-k} \quad t = 1, \ldots, T \]

Experience Curves and Prospective Approaches

<table>
<thead>
<tr>
<th>Approach</th>
<th>Role of Experience Curve Studies</th>
<th>Disadvantage(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Science and Technology Foresight</td>
<td>Not an obvious tool, since societal dialogue is the essential feature.</td>
<td>N. A.</td>
</tr>
<tr>
<td>Technology Forecast</td>
<td>One important tool, together with other trend extrapolation methodologies such as regression analysis and s-curve analysis.</td>
<td>Reliable technological data is seldom available. Can only be used for a series of incremental changes. Major shifts in technology cannot be predicted. Must be combined with scenarios or Delphi techniques.</td>
</tr>
<tr>
<td>Technology Assessment</td>
<td>Not an obvious tool since societal dialogue and assessments of the consequences of new technologies are essential.</td>
<td>N.A.</td>
</tr>
<tr>
<td>Science and Technology Policy Evaluation</td>
<td>One among several tools for analysing the impact of S&amp;T policies in a historical perspective.</td>
<td>Reliable technological data is seldom available. Must be combined with interviews, case studies, etc.</td>
</tr>
</tbody>
</table>
Empirical Data

- Danish wind turbines (1981 - 2000)
- 3226 turbines (50% of the turbines installed in Denmark)
- Data:
  - Year of installation
  - Manufacturer
  - Turbine type
  - Rated power (kW)
  - Rotor diameter (m)
  - Hub height (m)
  - Annual production at a reference site (ref. wind speed (m/s), ref. height (m))
  - Number of installed units
  - Turbine prices
  - Cost of foundation

Investment Cost Prediction

<table>
<thead>
<tr>
<th>Prediction Intervals</th>
<th>Obs.</th>
<th>Constant</th>
<th>Experience Parameter</th>
<th>Prediction</th>
<th>Lower Prediction Interval</th>
<th>Upper Prediction Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981-1985</td>
<td>5</td>
<td>1.03</td>
<td>-0.04</td>
<td>0.76</td>
<td>0.37</td>
<td>1.34</td>
</tr>
<tr>
<td>1981-1988</td>
<td>8</td>
<td>1.33</td>
<td>-0.12</td>
<td>0.53</td>
<td>0.27</td>
<td>1.03</td>
</tr>
<tr>
<td>1981-1994</td>
<td>14</td>
<td>1.62</td>
<td>-0.17</td>
<td>0.42</td>
<td>0.24</td>
<td>0.74</td>
</tr>
</tbody>
</table>
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SESSION 6: IMPORTING IDEAS
More Detailed Experience Curve

\[ A \cdot X^{-E} \]
\[ B \cdot X^{-E} \]
\[ C \cdot X^{-E} \]

Other Methods

- Innovation System Dynamics
  - Lifecycle: design, manufacturing and use

- Mapping or Relevance Trees

- Diffusion Modelling, S-Curves and Analogies

- Scenarios
  - Descriptive and normative

- Delphi Studies
  - Questionnaires from experts
Concluding remarks

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<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

Predictions

- Prediction of the cost level for wind power in 1995 with the use of 5 observations
Predictions

- Prediction of the cost level for wind power in 1995 with the use of 8 observations

![Graph showing investment cost (€/MW) vs. accumulated capacity (MW)]

Predictions

- Prediction of the cost level for wind power in 1995 with the use of 14 observations

![Graph showing investment cost (€/MW) vs. accumulated capacity (MW)]