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Deriving future support schemes of RES, by considering the cost evolution of RES technologies at volatile energy and raw material prices accompanied by technological learning impacts

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Abstract

Increasing the RES share in order to meet the European target (Directive 2009/28/EC) of 20% RES by 2020 is currently high on the agenda of European policy makers. This implies effective and efficient policy support measures whereas efficiency is determined by the real generation costs of renewable energy technologies versus the eligible total level of income from selling the produced energy. Hence, it is the final aim of this research to invent a support scheme of RES taking into account besides the technological learning effect also the influence of raw material prices in order to set the right incentives to potential investors.

A necessary step towards a more efficient RES support scheme is a more precise tool for calculating future forecasts of RES investment costs development. In this respect, this paper focus on various novel approaches of technological learning as well as the associated boundary conditions and related efforts need to be taken in order to integrate these approaches to the existing simulation tool ***Green-X***.

Introduction

As observed in several countries worldwide, energy policy is the main driver for the enhanced renewable energy deployment. Now, to the first time in Europe, binding targets for renewable energy sources (RES), regardless the energy sector, have been set – 20% RES up to 2020 indicates a huge future challenge for upcoming years. Despite, efforts have to be taken in all three energy sectors, Member States are free to decide their sectoral contribution. Since the national targets are allocated uneven, accordingly to their RES share in 2005 and a flat rate approach, new RES Directive 2009/28/EC foresees different flexibility. However, efficient and effective support measures have to be implemented in order to accompany a strong increase in the RES share with low transfer costs for the society.

An important parameter for efficient RES support schemes is the incorporation of expected evolution of generation costs of RES technologies. Since this development is influenced by several different input factors, showing a volatile historic development, this paper put special emphasis on the

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approach of determining the future development of overall RES investment costs. In this respect, mainly technological learning effects and the impact of volatile energy and raw-material prices is addressed. It is the task of this analysis of the development of future RES investment costs, to contribute to the further integration of such methodological approaches to the existing RES simulation tool ***GREEN-X***. This aims to allow a reshaping of support instruments of future RES installations.

Methodology and Status Quo

The model ***Green-X*** has been developed by the Energy Economics Group (EEG) at Vienna University of Technology in the research project “Green-X – Deriving optimal promotion strategies for increasing the share of RES-E in a dynamic European electricity market”, a joint European research project funded within the 5th framework program of the European Commission, DG Research (Contract No. ENG2-CT-2002-00607). Initially focused on the electricity sector, this tool and its database on RES potentials and costs have been extended within follow-up activities to incorporate renewable energy technologies within all energy sectors and up to the time horizon of 2030.

Green-X covers geographically the EU-27, and allows to investigate the future deployment of RES as well as accompanying cost – comprising capital expenditures, additional generation cost (of RES compared to conventional options), consumer expenditures due to applied supporting policies, etc. – and benefits – i.e. contribution to supply security (avoidance of fossil fuels) and corresponding carbon emission avoidance. Thereby, results are derived at country- and technology-level on a yearly basis. The time-horizon allows for in-depth assessments up to 2020, accompanied by concise out-looks for the period beyond 2020 (up to 2030).

Within the model, the most important RES-Electricity (i.e. biogas, biomass, biowaste, wind on- & offshore, hydropower large- & small-scale, solar thermal electricity, photovoltaics, tidal stream & wave power, geothermal electricity), RES-Heat technologies (i.e. biomass – subdivided into log wood, wood chips, pellets, grid-connected heat -, geothermal (grid-connected) heat, heat pumps and solar thermal heat) and RES-Transport options (e.g. first generation biofuels (biodiesel and bioethanol), second generation biofuels (lignocellulotic bioethanol, BtL) as well as the impact of biofuel imports) are described for each investigated country by means of dynamic cost-resource curves. This allows besides the formal description of potentials and costs a detailed representation of dynamic aspects such as technological learning and technology diffusion.

The simulation tool ***Green-X*** is based on a dynamic cost approach, taking into account future cost reductions to the enhanced development of RES technologies. These technology specific costs declines are mainly driven on the one hand by technological learning effects and on the other hand by the impact of raw material prices. Currently, the model considers a one factor learning curve which implies a cost reduction of a certain percentage with each doubling of energy generated (see Junginger et al, 2009). Hereby, for novel technologies like Photovoltaic or tidal and wave energy, typically higher learning rates than mature technologies like wind onshore energy or even large scale hydro power are expected. As mentioned above the overall technological learning effect depends on apart from the learning rate on the amount of energy generation on global scale, since most technological learning takes place globally. With respect to renewable energy generation these figures are calculated endogenously in the simulation tool Green-X whereas with respect to the overall generation abroad the EU27 it is based on the IEA WEO 2008. Additionally, the influence of energy and raw material prices on the investment costs of RES technologies, as recently strongly observed for the influence of the steel price on wind turbines, is currently still considered only by exogenous adjustment based on empirical records. In this context, the impact of increasing raw-material prices might compensate the effect of technological learning partly or even completely. Figure 1, below, indicates the resulting prediction of RES technology cost evolution in the electricity sector exemplarily according to a policy scenario. On the one hand, the mentioned impact of increasing steel prices on the wind energy converters is depicted in the figure and on the other hand, the rapid decrease of investment cost of novel RES technologies in the solar sector is noticed.

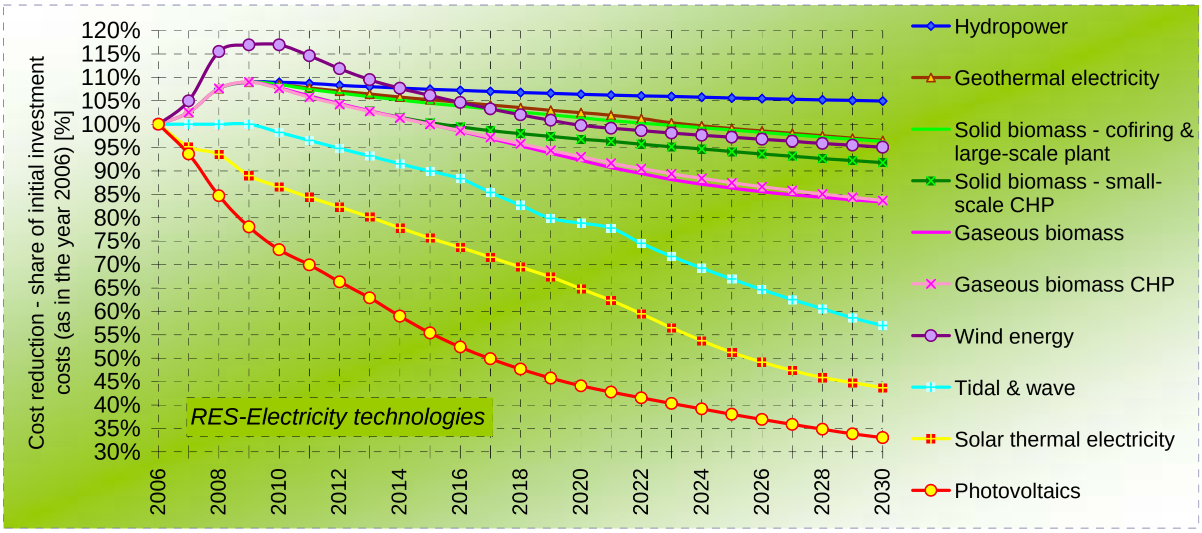

Figure 1 Expected cost development of RES technologies in the electricity sector up to the year 2030, taking into account technological learning effects and volatile energy and raw material prices; Source: Green-X database, 2009

Theory of learning approaches and the impact of energy and raw material prices

Current investment costs of energy technologies, especially renewable and hence partly mature technologies, are considered to decrease over time mainly due to technological learning effects. In this context, already early studies (see Wright, 1936 and BCG 1968) developed a mathematical description of the cost reduction per unit depending on the cumulative production based on technological learning effects. Herein a constant decrease of investment costs was observed with each doubling of cumulated production.

$$c(x_t) = c(x_0) \cdot \left(\frac{x_t}{x_0} \right)^{-b} \qquad \textbf{Eq(1)}$$

In Eq(1) x_t is the cumulative production, respectively the cumulated generation, $c(x_t)$ represents the costs per unit of production or generation at x_t and b stands for a positive learning parameter. Additionally, x_0 and $c(x_0)$ are indicating the cumulative production and the associated costs at an arbitrating starting point of the investigations. The resulting learning rate is then calculated by the term

$$LR = 1 - 2^{-b}. \qquad \textbf{Eq(2)}$$

Thus, on a double logarithmic plot the cost reduction assumed due to technological learning appears then as a linear function of cumulative production, respectively generation. Empirical research has shown that average learning rates of energy technologies are in the level of about 19% with a statistically test R^2 of 0.76 (see Ferioli et al, 2009).

Based on empirically determined technology learning rates for certain energy technologies the overall required investment in order to achieve the market competiveness of the technology can be derived by calculating the surface between the predicted investment cost line of the technology and the market reference price where the technology is integrated. Hence, the usage of historically determined learning rates for future forecasts of investment costs is very sensitive to the resulting learning investment. Additionally, calculating learning rates based on historic observation only over a short period of production or respectively generation might lead to an overestimation of the learning effect, since the more novel a technology is the stronger is the technology learning impact. This fact leads to wrong forecast of future cost evolution of energy technologies which is the relevant parameter for the energy technology installations considered in conducted energy scenarios. Moreover, as already indicated by the Club of Rome (1972) technological learning, especially in the energy sector, cannot be unlimited applied due to the technical restriction of the overall needed capacity in the energy sector.

In this context, historic records of investment cost evolutions of different energy technologies as presented by Junginger 2005, show different cost developments for certain periods which is not in line with the overall theory of a constant cost decrease with each doubling of cumulative installation or generation. Hence, this fact might indicate that either the determination of the overall learning rate was based on wrong data input or there are other influencing factors for the investment cost development.

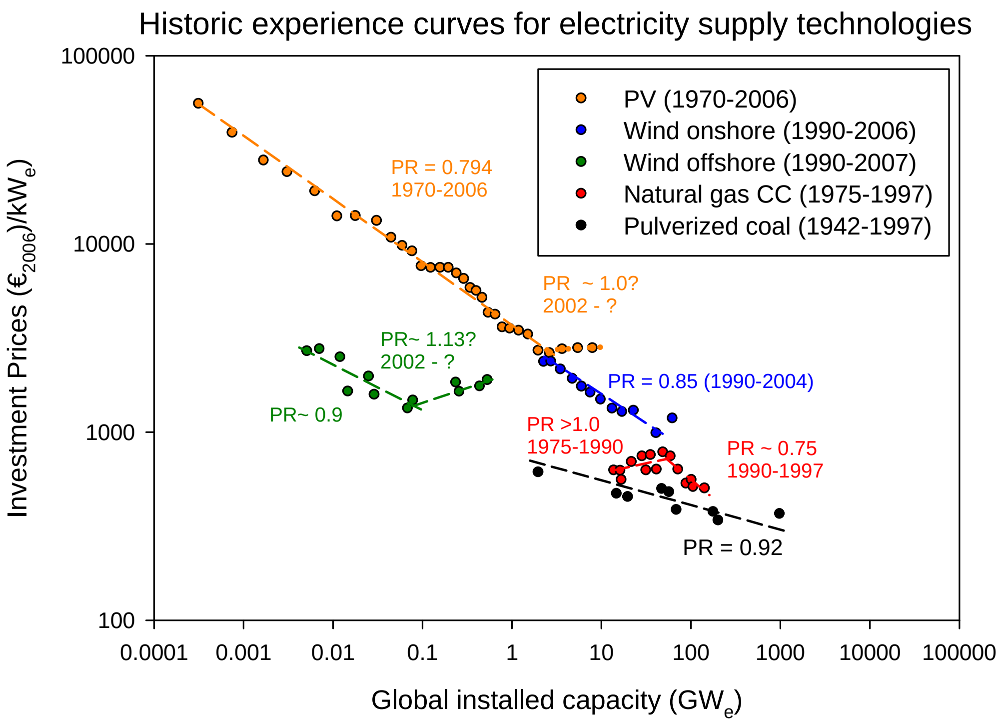

Figure 2 Learning curves of various electricity generation technologies in dependence on the global installed capacity versus the historic records of investment price evolutions (Junginger et al, 2005)

Above, Figure 2 depicts a constant decrease of investment prices for various electricity generation technologies over some orders of magnitude of cumulated capacity but especially for renewable electricity generation technologies as well an increase of investment prices beyond 2002. Since it is not assumed that technology learning will slow down or even turn in forgetting within this short time frame, it became obvious that a simple one factor learning curve based on learning by doing cost reduction does not seem to be appropriate for more precise investment cost forecasts of energy technologies. Therefore, other parameters as the influence of energy and raw-material prices as well as the demand increase for certain technologies should be considered as well as the in literature often mentioned learning by searching effect (see Berglund & Söderholm (2006)). Generally, the overall development of the future demand of certain energy technologies did historical have an important impact on development of energy technology investment prices but is very difficult to predict, and hence model emphasis within this paper is put on the impact of volatile energy and raw material prices as well as advanced concepts for the description of the technological learning effects.

Splitting the overall learning effects in learning by doing, based on cumulative production, and learning by searching, referring to accumulated knowledge leads to a more precise approximation of investment cost evolution of energy technologies.

$$c(x_t) = c(x_0) \cdot \left(\frac{x_t}{x_0} \right)^{-b} \cdot KS^{-LS} \qquad \textbf{Eq(3)}$$

In Eq(3) the same abbreviations are used as in Eq(1) above whereas additional the learning by searching effect is considered in KS representing the R&D based knowledge stock and LS stands for the associated positive learning parameter of R&D based knowledge.

Equation Eq(3) indicates that the two-factor learning curve approach addresses the fact that the investment cost evolutions of energy technologies are explicitly and directly related to both, the cumulated production (which is an indicator for experience) as well as to the cumulated R&D efforts. Regarding the R&D based knowledge stock KS as a first approximation the cumulative R&D expenses directed towards a specific technology can be considered. In a more detailed approximation the delay of spent R&D expenditures must be taken into account by determining the factor KS, addressing the fact that knowledge tends to depreciate in the sense that the impact of past R&D expenses gradually decreases.

However, recent observations have shown strong correlation of the evolution of investment costs for, almost all energy technologies to the development of commodity prices like steel, silicon or concrete. Figure 3 depicts the development of wind turbine prices compared to the real evolution the steel price in the same time period. Although steel as well as wind turbine prices only peaked beyond the time period of the figure, the correlation of two cost developments equals 0.89.

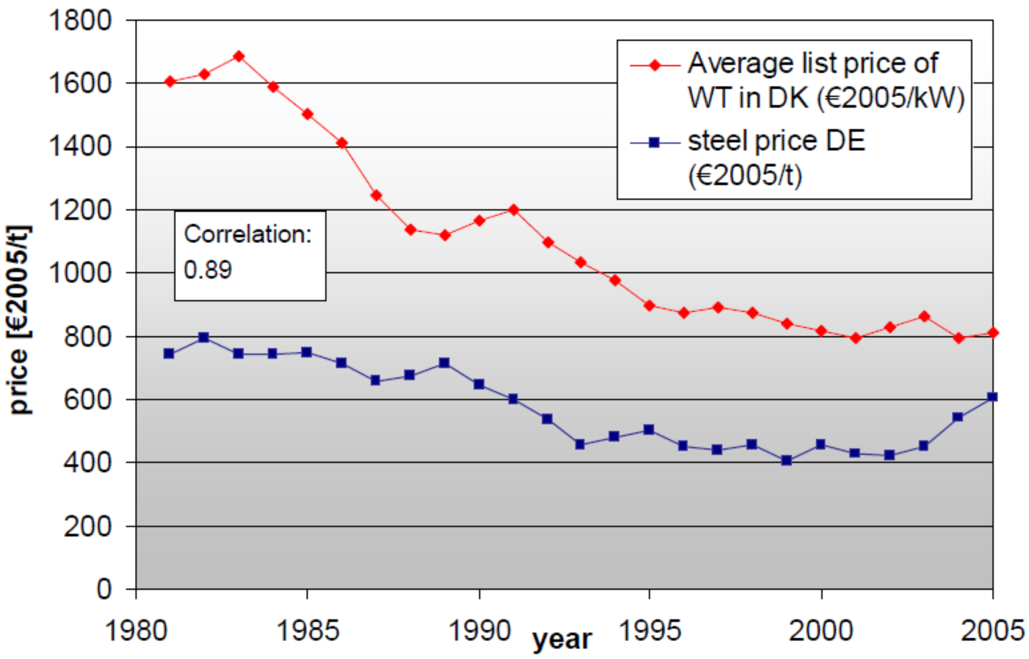

Figure 3 Historic development of steel price compared to the average list price of wind turbines from 1980 to 2005 in real Euro of 2005; Source: Floz et al, 2008

Hence, in order to more precisely approximate the overall learning development in the past and calculate cost evolutions forecast for the future the following approach of learning effects will be investigated.

$$c(x_t) = c(x_0) \cdot \left(\frac{x_t}{x_0} \right)^{-b} \cdot CP^{LCP} \qquad \textbf{Eq(4)}$$

Again, Eq(4) uses the same abbreviations as Eq(1) whereas in the additional term CP stands for Commodity price and the positive parameter LCP represents the impact factor of the commodity price on the overall investment cost evolution of the energy technology. Thus, a positive LCP indicates an increase of the investment costs for the certain technology due to increasing commodity prices and hence compensates the technological learning effect whereas a negative LCP even supports the technological learning effect and accelerates the overall investment cost reduction.

Considering the price development of the most relevant commodities for PV installations, silicon and silver, as shown in Figure 4, show a tremendous price decrease based on several circumstance in the early stage and hence contributed significantly to the overall cost drop of PV installations in this time period, illustrated in Figure 2. In contrast, the price increase of these commodities beyond 2002 compensated the technological learning effect completely and led to an overall stabilization of PV investment costs, as depicted in Figure 2. Thus, when calculating investment cost forecasts for energy technologies it is crucial to consider both, the technological learning effect and the influence of commodity price instead of either or.

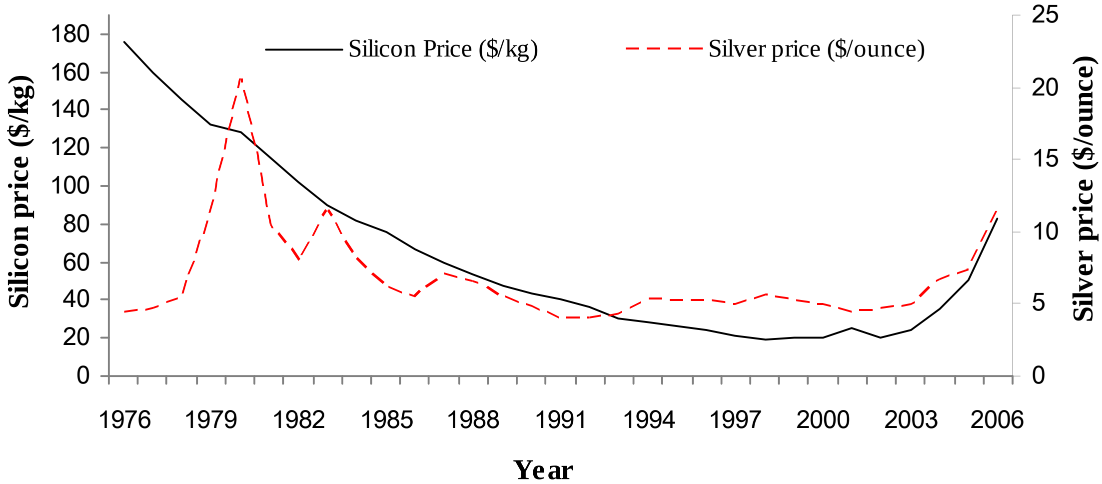

Figure 4 Development of silicon price and silver price between 1976 and 2006; Source: Yu et al, 2010)

Finally, as discussed in (Ferioli et al, 2009), the simultaneously technological learning of some components of an energy technology are applied in different energy technologies, is important to be taken into account by identifying the learning effect. This becomes of special relevance for more mature technologies when the overall learning effect is limited due to very hardly any opportunity for future doubling of the overall capacity but several small components within the technology might have this potential for a future doubling of the capacity caused by simultaneously use in various energy technologies. Hence the overall cost development equals the sum of the cost development of the components depicted in the formula Eq (5) below using the same abbreviations as Eq(4).

$$c(x_t) = \sum_{i=0}^{n} c(x_{0i}) \cdot \left(\frac{x_{ti}}{x_{0i}} \right)^{-b_i} \cdot CP^{LCP_i} \qquad \textbf{Eq(5)}$$

Practical implementation approach and assumptions

Building on the current status of the simulation tool ***Green-X***, modeling the impact of policy options on the renewable energy development, it is the objective of this paper to discuss the concept of refining the approach of technological learning and taking into account the impact of energy and raw material prices on the investment costs of renewable energy technologies.

Principally as discussed in prior, currently the model considers a one factor learning curve which implies a cost reduction of a certain percentage with each doubling of energy generated. Hereby, novel technologies like Photovoltaic or tide and wave energy, faces higher learning rates than mature technologies like wind onshore energy or even large scale hydro power. As mentioned above the overall technological learning effect depends on apart from the learning rate on the amount of energy generation on global scale, since most technological learning takes place globally. With respect to renewable energy generation this figures are calculated endogenously in the simulation tool ***Green-X*** whereas with respect to the overall generation abroad the EU27 it is based on the IEA WEO 2008.

Based on the status quo, the following new approaches will be implemented in the modeling tool:

Learning by doing accompanied by learning by searching:

Separating the technological learning effect in learning by doing and learning by searching derives very important insights for policy decision making since the direct impact of (public) R&D expenditures can be quantified. However, these results are very sensitive to the input data of R&D expenditures. Moreover, this methodology contains more degrees of freedom resulting in more unknowns than the standard experience curve, thus potentially increasing the error. In this context, on the one hand data gathering for R&D-related information is very difficult, especially of business R&D expenditures, since these data is mostly treated confidentially. On the other hand, it might as well be difficult to allocate public R&D expenditures to the individual energy technologies.

Consequently, separating the influence of learning by doing and learning by searching will not be considered for all energy technologies, respectively their components in the model. However, due to the policy relevance this approach will be pursued for a mature renewable energy technology (i.e. wind energy) apart from the integration to the simulation model. In order to ensure confidence of the achieved results, the impact of separate learning by doing and learning by searching needs to be statistically tested and compared to overall technological learning effects found in literature. As elaborated by Folz, 2008 first results in this context indicate that learning-by-searching has a strong effect on the cost reduction of wind turbines. It could even be higher than the effect of learning-by-doing but due to the small sample size and the uncertainties in the data, however, the results should be interpreted carefully.

Component learning for mature RES technologies:

In consequence of above mentioned limits of learning effects for total energy technology installations, the component learning approach will be implemented for more mature technologies like hydro power, wind energy, and biomass energy converters. It is envisaged to cluster several components for which a technology learning rate will be determined based on empirical studies. In this respect, the development of one technology cluster in other than the renewable energy sector has to be considered as well, as for instance turbines applied in biomass plants as well as in gas-fired power plants.

In order to determine the different component clusters of an energy technology the total share of costs of the certain component of the total plant has to be indentified. This allocation will be based on empirical studies conducted for instances by Schumacher (2010). In this approach, the share of each component of the total energy technology is an exogenous parameter for the model. Consequently, any potential shift of the certain components shares, caused by i.e. material substitution has to be adjusted manually in the model. Figure 5 illustrates the share of investment cost for a wind onshore and wind offshore energy converter according to its components.

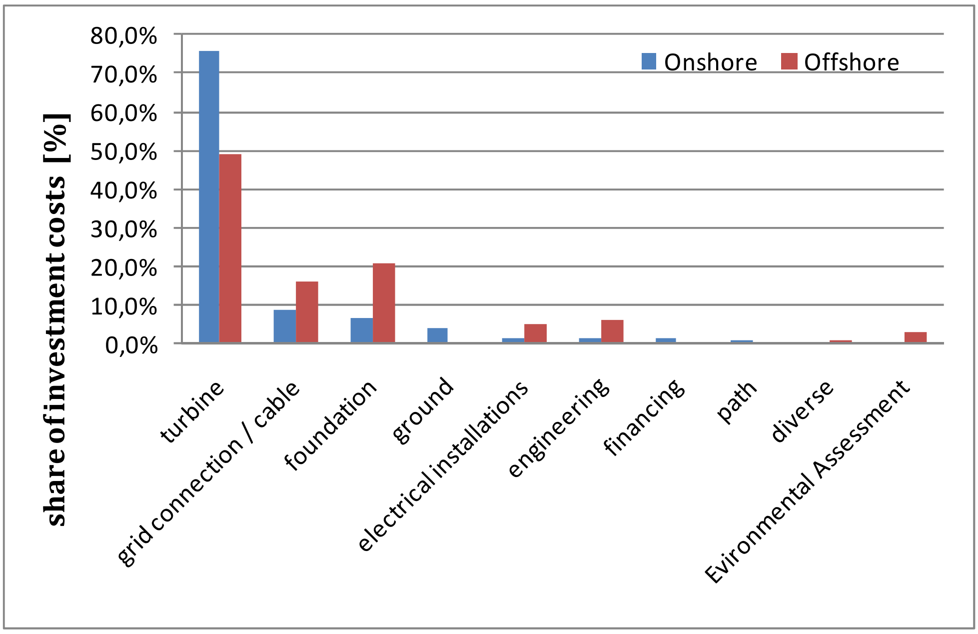

Figure 5 Share of investment cost of a wind energy converter according to its components. Blue (left) bar represents an onshore converter & red bar (right) an offshore converter; Source: Schumacher et al, 2010

A major task with respect to the component learning approach is the data gathering process required to identify the certain technological learning effects. On the one hand learning rates for each component have to be derived from historical observations and on the other hand the overall installed capacities need to be identified. For the latter, the installed capacities within the EU 27 Member States are calculated endogenously but for the rest of the world, international statistics have to be taken into account. Since not of all of these data will be available in the current reference, the IEA WEO, other statistics will be considered, whereas the consistency of data is a precondition. Additionally, the status quo of each cluster in terms of costs per unit as well as globally installed capacities needs to be identified in order to form the starting point of the technological learning effect of each component cluster. Due to the huge amount of data required for this approach, not more than three component clusters per technology are envisaged to be investigated. As far as possible these technologies will be separated to component clusters according to combustor, turbine and construction.

Although this approach allows a more precise determination of the overall technological learning forecasts under the consideration of the limits, certain boundaries have to be taken as well. In this respect, in the literature it is argued that only considering the technological learning effect of each component clusters, and then adding up these figures to the overall future investment cost evolution for each technology, neglects the learning of mounting all components to one energy technology as it is then integrated to market.

Two factor learning curve, considering the impact of energy and raw material prices:

Finally, the current approach with respect to technological learning effects of the simulation tool ***Green-X***, based on a one factor learning curve will be extended to a two factor learning curve, considering additionally the influence of raw material prices. In this context, the most crucial raw materials for renewable energy technologies have been identified as steel, silicon and concrete as well as copper, silver and aluminum. Depending on the specific energy technology, the most important materials will be considered in the model for determining the future cost development of the energy technology itself. Since the definition of the specific raw material price is an exogenous parameter for the simulation model the reference source has to be decided very carefully, especially caused by the fact that recent observation have shown very volatile energy and raw material prices. Exemplarily, Figure 6 highlights the historic development of the real steel price in Euro/ton of 2000 for the last ten years showing a big peak in 2008.

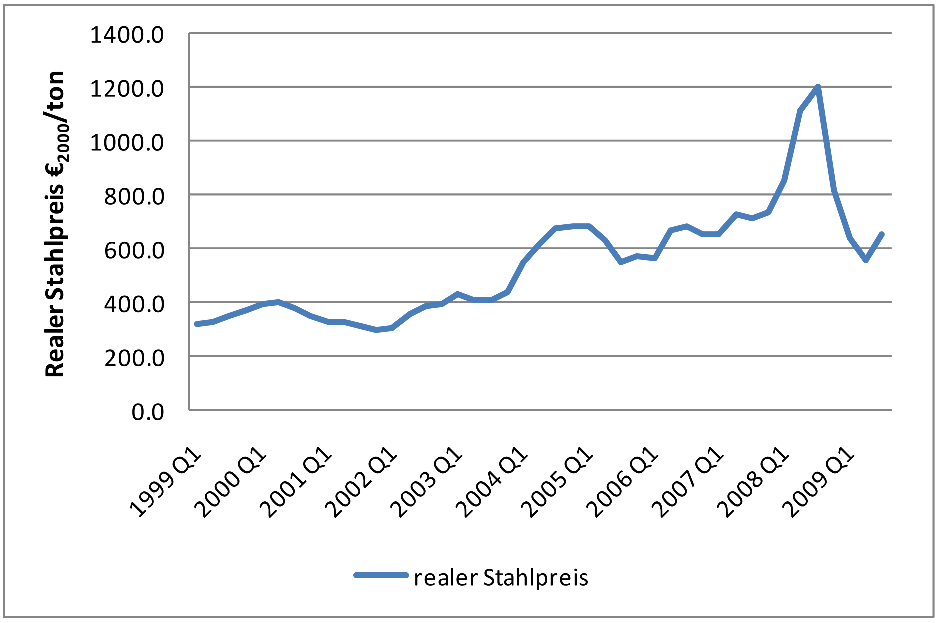

Figure 6 Global steel price index development between 1999 and 2009, Source: CRU Group, 2009; Source: Schumacher et al, 2010

On the one hand, arguments exist to link the development of the raw material prices to the development of the oil price, which showed a high correlation in the recent past, but on the other hand the increase of the real steel price, in Figure 6, was mainly driven by the tremendous demand increase in China and India and only to a minor extend influenced by the oil price. However, the global development of supply and demand of each relevant raw material is far beyond the scope of the simulation model ***Green-X*** and hence, cannot be taken into account here. Therefore, an opportunity to incorporate the influence of raw material prices best could be to consider two raw material price scenarios, one with a moderate development and the other with a strong increase of raw material prices showing very volatile dynamics.

Moreover, the impact of a specific raw material price on the overall investment costs of energy technology has to be indentified. This share is determined based on empirical studies and forms an exogenous parameter for the model. However, these shares have to be defined according to the components structure presented above. Hence, a huge amount of data needs to be collected whereas, at least the share of raw material influence is in most cases treated confidentially and therefore forms a barrier for a high resolution. In addition, in a dynamic modeling approach not only the impact of raw material prices on total investment cost of renewable energy technologies is important but also the total share of raw materials on the energy technology in quantitative terms. Strong increase of raw material prices might lead to material substitutions in the development of the energy technology and consequently reduces the impact of the material price. Since material substitutions based on R&D experience are impossible to model, the material substitution caused by material price increases will be considered by setting thresholds where a material substitution is very likely to take place. Again such material substitution can only be considered between two already now competing materials which are already established on the market.

Expected results

The simulation tool ***Green-X*** models the impact of policy support options on the future development of renewable energy source within the EU in quantitative terms as well as in terms of investments needed and the related policy costs for the society. In this context, the investment cost forecast is a crucial part since it determines the long-run marginal costs of each energy technology and consequently the decision process which technologies are being installed according to the scenario objective. Due to recent observation of increased investment costs of certain energy technologies deviations from the real cost development to the forecast based on a one factor learning curve are being noticed. Thus, a two factor learning curve, considering the impact of volatile energy and raw material prices results in a much better fit, since technological learning effects and raw material influences are addressed in a common manner as shown by Yu et at. (2010) in Figure 7.

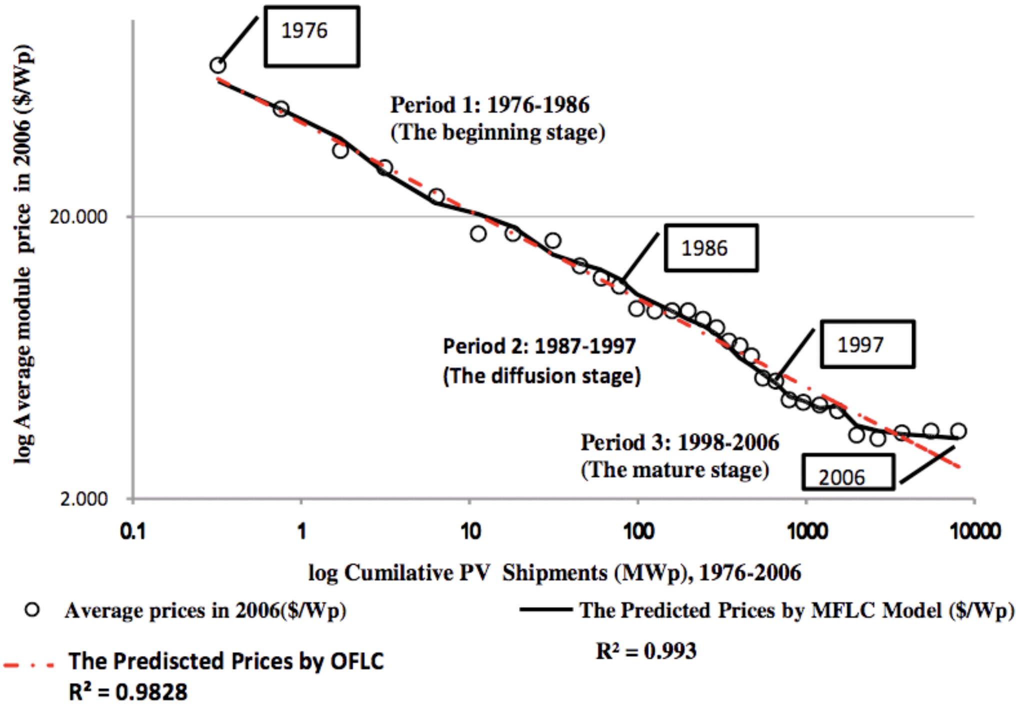

Figure 7 Development of historic PV module price in doted line compared to approximations based on a one factor learning curve (red line) and a two factor learning curve considering the silicon price as well (black line); Source: Yu et al, 2010

The additional separation of component clusters for each renewable energy technology allows for a more precise consideration of technological learning effects. The relevance of the component learning approach is highly seen in more mature energy technologies, where the overall learning effect is limited by non-economic issues, i.e. no doubling of installed capacity feasible.

Finally, increasing the RES share in order to meet the European target (Directive 2009/28/EC) of 20% RES by 2020 implies effective and efficient policy support measures. In this context, the efficiency of RES support schemes is determined by the real generation costs of renewable energy technologies versus the eligible total level of income from selling the produced energy. Hence, it is the final aim of this research to invent a support scheme of RES taking into account besides the technological learning effect also the influence of raw material prices in order to set the right incentives to potential investors. In this respect, the level of support can be adjusted according to the current market situation. Consequently, this will allow to increase the efficiency of the support scheme by reducing the level of support in times of low raw material prices but increasing the support level again in times of high raw material prices in order to attract investors and enable a constant growth of RES in the future.

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