What about the long term? Using experience curves to describe the energy-efficiency improvement for selected energy-intensive products in Germany

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Abstract

We analyse the long-term energy efficiency trends of selected energy-intensive production processes in Germany in the second half of the 20th century. The processes we consider are the pulp and paper industry, the production of crude steel, cement, and primary aluminium. Together they represent about 34 % of the energy consumption in the German industry.

To analyse the time series, we use the experience curve approach, which is widely used for assessing the dynamics of specific costs for energy technologies, but has so far only rarely been applied to analyse energy-efficiency developments. We use the specific energy consumption as an indicator of the energy efficiency improvement and the cumulative production as an indicator of experience.

The results show learning rates in the range of 3.5–9.5 % for the specific primary energy consumption, that is doubling the cumulative production volumes results in 3.5–9.5 % lower energy consumption. Using available forecasts for industrial production shows efficiency improvements of 4.0 % by 2020 and 6.9 % by 2035 compared to 2007 as the average across all processes considered.

Further, the results reveal huge improvements in energy efficiency for the period after WW2 and a rather slow improvement in the last two decades for many processes. Energy efficiency has improved more for fuels than for electricity. In general, energy efficiency improved fast, when new processes entered the market as for example for electric steel and hardly improved for very old and mature processes like clinker burning or primary aluminium smelting.

In order to improve the robustness of these first analyses and conclusions follow-up studies looking at other processes, products and industries and also countries are certainly necessary.

Introduction

While improving energy efficiency is a central goal of European energy policy which is also included in the EU's 20-20-20 targets, there is a discussion about how much the individual demand sectors can contribute to these targets and beyond. For the entire EU, the industry sector contributed to about 25 % of final energy demand in 2010 and also in Germany the share of industry has remained more or less constant at about 30 % in recent years. Consequently, efficiency improvement in the industrial sector is essential. It is, however, unclear how much the industrial sector can contribute – in Germany as well as in the EU or globally. Particularly representatives from energy-intensive industries have often emphasised huge energy-efficiency improvements in the past, which supposedly do not leave much room for further future improvement, even in the long term.

Studies assessing energy efficiency potentials use various approaches. Some follow a benchmarking approach by comparing the average energy intensity in sectors or countries with best practice technology. Such an approach is used by Saygin et al. (2011), who find a global energy efficiency improvement potential in the energy-intensive processes of about 27 % by replacing all existing plants with best practice. About three quarters of this potential is available in developing countries. As they also mention, this approach does not cover improvement potentials from innovative technologies not yet on the market. Other studies are based on a bottom-up assessment of individual technologies including innovations. For example Worrell et al. (2000) calculate a cost-effective energy saving potential of about 18 % for the US cement industry. De Beer et al. (1998) assess the impact of innovative technologies on the energy efficiency in iron and steel making. They conclude that the specific energy consumption of making steel from iron ore can be reduced to 12.5 GJ/t of crude steel compared to the world average of 24 GJ/t in 1990. Similar studies have been conducted for various sectors and countries (e.g. Hasanbeigi et al. 2010). Some very detailed bottom-up simulations even explicitly consider the turnover of the capital stock and the diffusion speed of energy-efficient technologies. Among those are two recent analyses of the European cement industry (Pardo et al. 2011) and the iron and steel sector (Pardo, Moya 2013). They found an energy efficiency improvement potential for thermal uses of around 11 % from 2010 to 2030 for cement. For oxygen steel, the potential improvement of the specific energy consumption is in the range of 7–11 %. For Germany, only few such studies are available which look at energy-saving potentials in energy-intensive industries. A broad assessment of most energy-intensive processes has recently been conducted (Fleiter et al. 2011; Fleiter et al. 2013) where the technical saving potential across all sectors was found to be around 14 % until 2035. For the German paper industry, Fleiter et al. (2012) calculate a technical energy efficiency potential of 16 % (electricity) and 21 % (fuels) until 2035.

While all these studies look at the long-term future, most do not at all take into account the past development or do this only for a rather short period of time. This is even more astonishing given the long capital lifetime in the energy-intensive industries. We take this as a starting point and contribute to the discussion of energy efficiency potentials by taking a look at the very long term and analysing the energy efficiency development for selected industrial energy-intensive processes during the 20th century. This includes the production of crude steel, cement, clinker, paper and primary aluminium. We followed a 3-step approach. First, we gathered data on the specific energy consumption (SEC) of the major processes and their annual production output to develop time series which are as long as possible. Often, data comes from various sources and the collected set of time series already provides new insights as such data has not been compiled before. Second, we use a classical "experience or learning curve" approach to analyse patterns in the SEC over time and across processes. We use the cumulated annual production output as a proxy for the cumulated experience. Our methodology allows us to compare learning rates and efficiency improvements in different industrial sectors. Third, we use the experience curve approach to forecast SEC until 2035 based on past observations.

The experience curve approach has been frequently used to forecast the specific costs of renewable energy technologies and their relation to their deployment, it has so far only rarely been used to analyse and forecast energy efficiency improvement. In line with this approach, we argue that it is rather the use and the application of a technology that results in efficiency improvement (via optimization, replacement and R&D) than the simple passing of time. Or as McDonald and Schrattenholzer (2001) call it: "Unlike a fine wine, a technology design that is left on the shelf does not become better the longer it sits unused."

The paper is structured as follows. We describe the learning curve approach applied in the next section, before we discuss the data used for each of the processes taken into account. Finally, we compare the learning rates calculated for the past and use them to forecast energy efficiency in the individual processes until 2035.

Method used

THE LEARNING CURVE APPROACH

The learning curve approach is initially based on the empirical observation that tasks are performed faster the more often they are repeated. This has been successfully applied to time and cost efficiency in manufacturing processes (Taylor and Fujita 2013). The later extension to total production and investment costs of new technologies modified the individual "learning-by-doing" effect to "technological learning" (Klaasen et al. 2005). In the last decade the learning curve approach has been adopted to study the decline of investment costs of energy technologies over time (IEA 2001, McDonald and Schrattenholzer 2001, Neji 2008, Hettinga et al. 2009). Besides the cumulative production, such studies also use the cumulative installed capacity or the cumulative sales as a measure of the experience gained. McDonald and Schrattenholzer (2001) found a median learning rate of 16–17 % for their data set of energy technologies, which represents the reduction of unit costs for each doubling of the cumulative production (or installed capacity). Most of the calculated learning rates are between 5 % and 25 %. In recent years, such analyses of cost dynamics have also increasingly been conducted for energy-demand technologies (Weiss et al. 2010a and 2010b, Jardot et al. 2009, Jakob and Madlener 2010, Schall and Hirzel 2012).

So far, the approach has been rarely used to analyse changes in energy efficiency over time. Chang et al. (2012) use the experience curve approach and explain changes in energy intensity as a function of cumulative global energy consumption. More specific to the industrial sector, Ramírez and Worrell (2006) have examined changes in SEC over time in the production of fertilizers in the US from 1961 to 2001. They used the cumulative production of fertilizers as an indicator of the experience gains. For ammonia they find a learning rate of 29 % and for urea of 12 %. Our methodology, as described in the following, is based on the approach of Ramírez and Worrell (2006), who are – to our knowledge – the first to use experience curves to analyse changes in the SEC of industrial processes over time.

STATISTICAL APPROACH

We use the One-Factor-Learning-Curve, eq. (1), which establishes a link between the energy efficiency, represented by the SEC, and experience in the production process measured as cumulative production CP. By taking the logarithm, the power function can be linearised, eq. (2).

$$SEC_t = SEC_0 * CP_t^b \tag{1}$$

$$\log SEC_t = \log SEC_0 + b * \log CP_t \tag{2}$$

Where:
SEC_t specific energy consumption in year t
CP_t the cumulative production in year t
SEC_0 SEC in the first year of production
b experience index

In the literature, different measures are used for the cumulative experience such as annual production, installed capacity or annual sales (McDonald and Schrattenholzer 2001). Our choice to use the annual production as a measure for experience has some methodological consequences. Taking the installed production capacity as a measure implicitly assumes that improvements due to better operation are not accounted for, whereas this is the case when using the annual production. This is relevant for Germany where little capacity expansion takes place in most energy-intensive industries. Also the regional scope plays an important role. While we consider production in Germany, learning might take place in other countries. This is not necessarily captured in the annual production and thus mostly outside our scope.

The learning rate LR describes the decrease in SEC when doubling the cumulative production and is calculated using the experience index b as follows.

$$LR = 1 - 2^b \quad (3)$$

Ordinary least squares regression is used to fit eq. (2) to the data. The non-linear transformation of eq. (1) to obtain the linear function eq. (2) leads to minor deviations when compared to the non-transformed data (see van Sark 2008). These deviations can be regarded as negligible when compared to other uncertainties. To quantify the statistical uncertainties we use the standard deviation of the LR σ_{LR} (see van Sark and Alsema 2006). Taking the highly aggregated data and in some cases necessary adjustments of the data into account, the results of the LR are indicated with an uncertainty of $2\sigma_{LR}$ (see Results section) The coefficient of determination R^2 is used to estimate the goodness of fit (Fahrmeir 2003).

Data used

In order to calculate learning curves, yearly production data and SEC data are required for as long as possible. While the availability of production data is quite good, this is different for the SEC values. Depending on data availability for the process, we have either calculated the SEC data as the average SEC of industries and products in Germany or we have taken SEC data of the best available global technology (BAT). Production data and average SEC data of industries and products in Germany are obtained from associations, while SEC data of the BAT can be found in the scientific literature. In the following, we discuss the data sources used per sector.

We have initially screened all sectors with energy intensities higher than 4 kWh per euro value added. Among these, we did not find sufficient data for the glass, ceramics and chemical industry, and did not include them in the analysis. In a second step, we identified the most energy-consuming processes within the selected sectors.

PULP AND PAPER INDUSTRY

We used production and average SEC data of the pulp and paper industry association's annual report (VDP). This publication contains production and final SEC data for the time period between 1955 and 2008. More detailed energy consumption data allowing statements about electrical, thermal, primary and final SEC is available for the years between 1973 and 2008.

The electrical SEC was calculated using the data of the total amount of bought-in electricity, own production from hydropower and photovoltaics, sales of electricity and the production data. The thermal SEC was calculated using data of the total amount of energy from fossil fuels and steam as well as the production data. Note that the auto-production of electricity using fuels is within the system boundaries of the pulp and paper industry.

The data contain energy consumption for the production of the final products from the raw materials wood and waste paper without finishing processes (see Figure 1). Based on this data source, it was not possible to distinguish individual paper grades.

CLINKER AND CEMENT

Production and energy-related data of the products clinker and cement have been made available by the German cement association (VDZ). In addition we used data from VDZ (2011 and 2013b) and complemented the production data using sales figures of cement published in BDZ (2000). Production and sales figures of cement are strongly correlated throughout the years for which both types of data are available. In some time periods (see Table 2) production data of clinker and thermal energy data of cement have been approximated by using the clinker factor (share of clinker in cement production) and the data of the corresponding product. Potential errors of a necessary assumption of the clinker factor have been estimated by variation of this factor and were added to the statistical uncer-

Table 1. Overview of the pulp and paper industry data.

Data type	Used time period	No. of data points	Data source	Comments
Production data	1955–2008	54	VDP annual report	Annual production data for Germany.
Final SEC data	1955–1970	4	VDP annual report	After 1970 the final SEC is calculated using the more detailed energy consumption data.
Energy consumption data	1973–2008	36	VDP annual report	Total amount of bought-in electricity, own electricity production from hydropower and photovoltaics, sales of electricity, thermal energy from fossil fuels and steam from district heating.

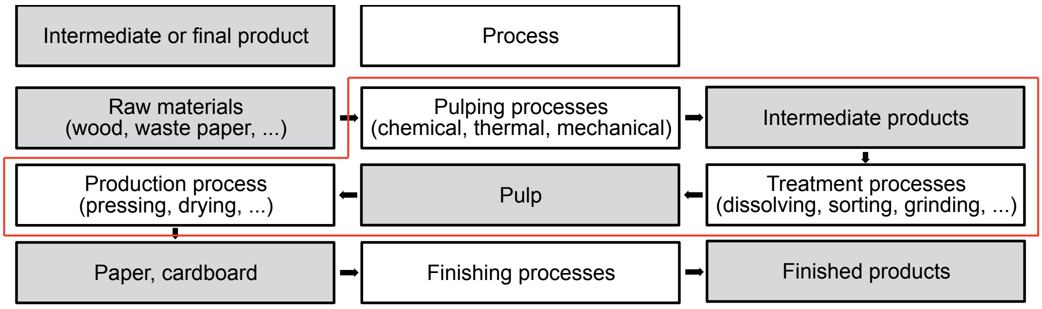

Figure 1. System boundaries of the SEC data of the pulp and paper industry. It includes the production of paper and cardboard from raw materials without finishing processes.

Table 2. Overview of the clinker and cement data.

Data type	Used time period	No. of data points	Data source	Comments
Production data cement	1961–2012	52	VDZ (2013a)	Annual production data for Germany.
	1951–1960	10	BDZ (2000)	Approximation using sales data.
Production data clinker	1979–2011	33	VDZ (2013a)	
	1951–1978	28	Approximation	Approximation using the clinker factor and the production data of cement.
Electrical SEC cement	1995–2012	18	VDZ (2013a)	
	1990–1994	2	VDZ (2013b)	Assumed linear rise in time period 1991–1993.
	1951–1989	39	VDZ (2011)	Values were determined graphically from figures.
Thermal SEC clinker	1951–2011	61	VDZ (2011)	Values were determined graphically from figures.
Thermal SEC cement	1997–2012	16	VDZ (2013a)	
	1990–1996	4	VDZ (2013b)	Assumed linear rise in time period 1991–1993.
	1951–1989	39	Approximation	Approximation using the clinker factor and the thermal SEC of clinker.

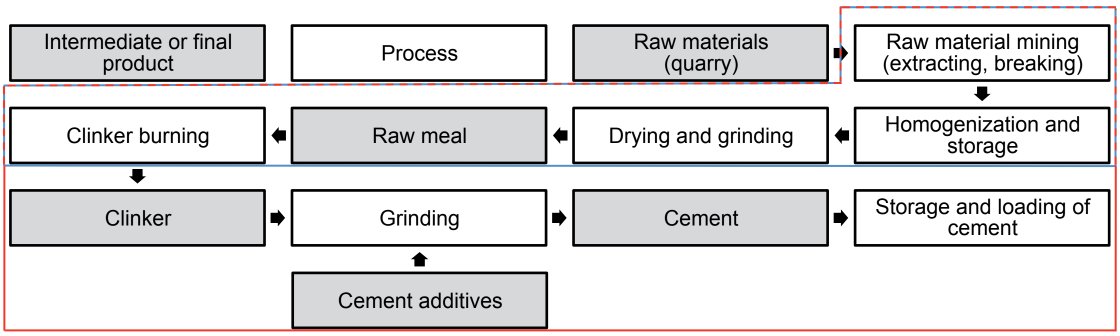

Figure 2. System boundaries of the SEC data of clinker and cement. Blue shows the system boundary of the clinker production process, including all processes from the raw material to the finished clinker. Red shows the system boundary of the cement production process. It includes the production and grinding of the clinker and other cement additives as well as the storage and loading of the finished product cement.

tainty. Based on the relation of the production output of clinker and cement in the time period in which both data are available, we assumed a clinker factor of 0.83. A variation of ±0.03 leads to deviations of the LR of <0.5 % which was conservatively rounded to ±1 %.

On the basis of these data and assumptions we compiled a data basis for clinker from 1951 to 2011 and for cement from 1951 to 2012. The process "clinker" is defined from the extraction of raw materials to the clinker kiln, while the process "cement" adds also the grinding of the clinker together with additives (see Figure 2).

STEEL

Various years of publication of the statistical yearbook of the German steel industry (WV-Stahl) were used for the production and primary SEC of crude steel for the time period between 1960 and 2011.

The data cover the production of crude steel (electrical steel, oxygen steel, Siemens-Martin steel and Thomas steel) from the raw materials steel scrap, coal and iron ore. Finishing like hot or cold rolling is outside the scope, (see Figure 3). The data for the SEC did unfortunately not allow distinguishing the individual production routes.

Table 3. Overview of the steel data.

Data type	Used time period	No. of data points	Data source	Comments
Production data	1960–2011	52	WV-Stahl	Annual production data for Germany.
Primary SEC data	1960–2011	52	WV-Stahl	The calculation method of the primary SEC could not be clarified.

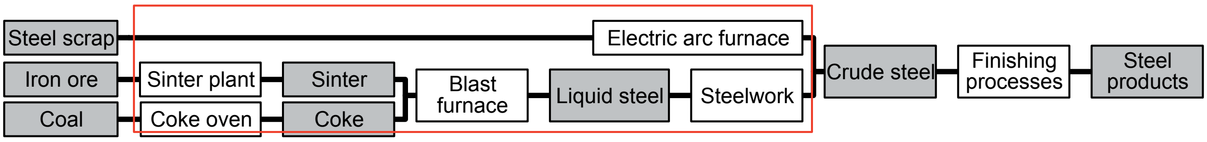

Figure 3. System boundary of the SEC data of crude steel. The outdated production of Thomas steel and Siemens-Martin steel are not presented in this figure but also within the system boundary of the crude steel production, which includes all production processes from the raw materials to crude steel.

Table 4. Overview of the primary aluminium electrolysis data.

Data type	Used time period	No. of data points	Data source	Comments
Production data	1947–2009	52	WBMS	Annual production data for Germany
Electrical SEC data	2009	1	IPPC (2009)	BAT, lowest value indicated
	2007	1	Worrell et al. (2007)	BAT, lowest value indicated
	2003	1	Dienhart (2003)	BAT, lowest value indicated
	2002	1	Quinkertz (2002)	BAT, lowest value indicated
	2001	1	IPPC (2001)	BAT, lowest value indicated
	1962–1995	16	Briem et al. (2000)	Parameters of newly installed electrolytic furnaces
	1961	1	Schmitt (1961)	Lowest value of a “modern” electrolytic furnace
	1953, 1955	2	Ginsberg (1958)	Lowest values of “modern” electrolytic furnaces
	1950, 2007	2	Schwarz (2008)	BAT
	1950–1978	5	Werner (1978)	Lowest values of “modern” electrolytic furnaces
	1947, 1967	2	Crussard (1978)	BAT

ALUMINIUM

The annually published statistics on metal production (WBMS) provide production data of primary aluminium since the beginning of aluminium production in Germany in the year 1898. Additional assumptions and the publications by Franke (1986), Lesclous and Fridenson (1999) and Krone (2000) have been used to fill gaps in these data (before 1947). SEC data are mainly available in the form of the electrical SEC for the BAT of the primary aluminium electrolysis process. We used the data sources listed in the following table to create a corresponding SEC data series. It contains data representing the BAT of the electrolysis process and parameters of newly installed or available electrolytic furnaces, and therefore, in contrast to the other surveys, worldwide values. Due to irregularities at the time of the First and Second World Wars, we decided to concentrate the following analysis on the data beginning with the year 1947.

In this case the system boundary includes only the primary aluminium electrolysis process. We further intended to compile data for the production of aluminium oxide and secondary aluminium, but the data collected are not sufficient for our analysis. Nevertheless, we state them in Table 5 as a reference for future research.

SUMMARY OF AVAILABLE DATA

To summarize, the SEC for the pulp and paper industry is based on the time series of energy consumption of the entire sector, for cement, clinker and crude steel it is based on product-related data, whereas the SEC for primary aluminium is based on literature values for the BAT. Thus, from pulp and paper industry to primary aluminium electrolysis the system boundary is also narrowed down.

For the analysis of a production process as a whole it is necessary to combine electrical and thermal energy to final or primary energy. Final energy data were obtained by adding up thermal and electrical energy. For primary energy data, the electrical share is tripled. This simplification was unavoidable since detailed data of the fuel mix needed for a better estimation were not available over the whole time period. In cases where only thermal or electrical energy data were available, final and primary energy have been approximated as these types of energy represent the dominant part of the total energy consumption in the corresponding production process. In this case, we assumed the missing energy carriers to be zero and final and primary energy has been calculated as described above. This was the case for clinker and primary aluminium

Table 5. Overview of other aluminium data. The evaluation of these data does not lead to robust results and is not discussed further.

Data type	time period	No. of data points	Data source	Comments
Production data aluminium oxide	1955–2011	57	WBMS	Annual production data for Germany
Production data secondary aluminium	1955–2011	57	WBMS	Annual production data for Germany
SEC data aluminium oxide	2009	1	IPPC (2009)	BAT
	2007	1	Worrell et al. (2007)	BAT
	2003	1	Dienhart (2003)	BAT
	2001	1	IPPC (2001)	BAT
	1996	1	Krone (2000)	BAT
	1981	1	Winkhaus (1981)	BAT
SEC data secondary aluminium	1975–1992	5	Kammer (2011)	Average values for Germany
	1975–1982	6	Erne (1984)	Average values for Germany

Table 6. Overview of data used.

Industry/product/process	Scope	Type of energy	Time period	No. of SEC data points
Pulp and paper industry	Sector	Final energy	1955–2008	4
		Electrical, thermal, final and primary energy	1973–2008	36
Cement	Product	Electrical, thermal, final and primary energy	1951–2012	59
Clinker	Product	Thermal energy	1951–2011	61
Crude steel	Product	Primary energy	1960–2011	52
Primary aluminium electrolysis	Process	Electrical energy	1947–2009	33

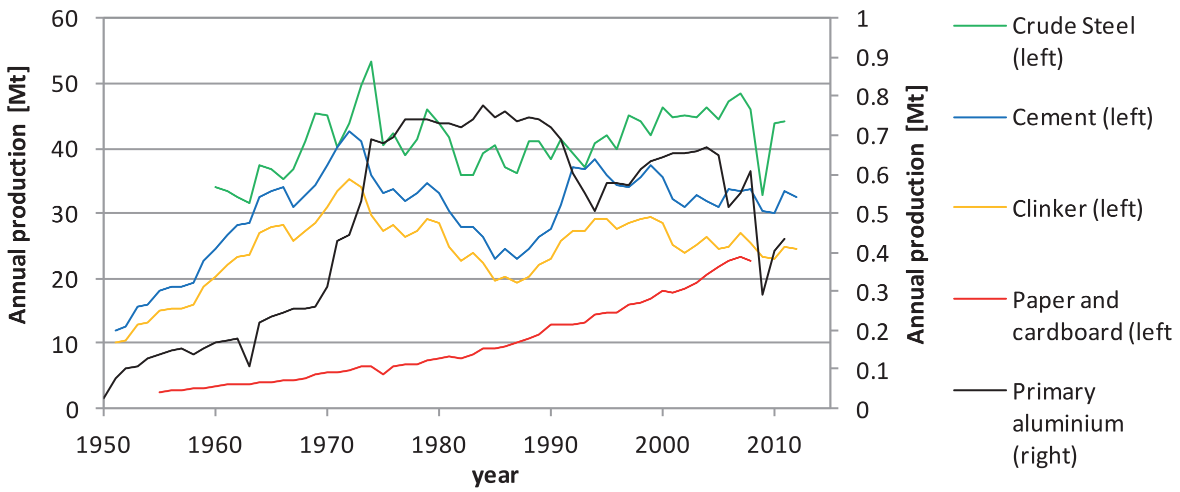

Figure 4. Development of the annual production output of the considered processes in Germany.

electrolysis. For the pulp and paper industry, cement and crude steel, data on all energy carriers was available and primary as well as final energy could be calculated without the need for additional assumptions.

Beside the SEC data we determined the annual production output of the considered processes which is presented in Figure 4. In total the products and processes covered in our study represent approximately a tenth of the total primary energy consumption of Germany and one third of the German industry. The development of the total primary energy consumption of the considered processes is shown in Figure 5.

Results

We used the learning or experience curve approach described above to model the specific energy consumptions within different industrial sectors and for different processes and energy types such as primary, thermal or electrical energy. The data can be presented as the absolute or relative evolution of SEC either as a function of time or – closer to the learning curve approach – as a function of cumulative production. Both abscissas will be used in the following, but for the dependent variable we will focus our attention on the evolution of SEC as compared to a base year, i.e. relative SEC.

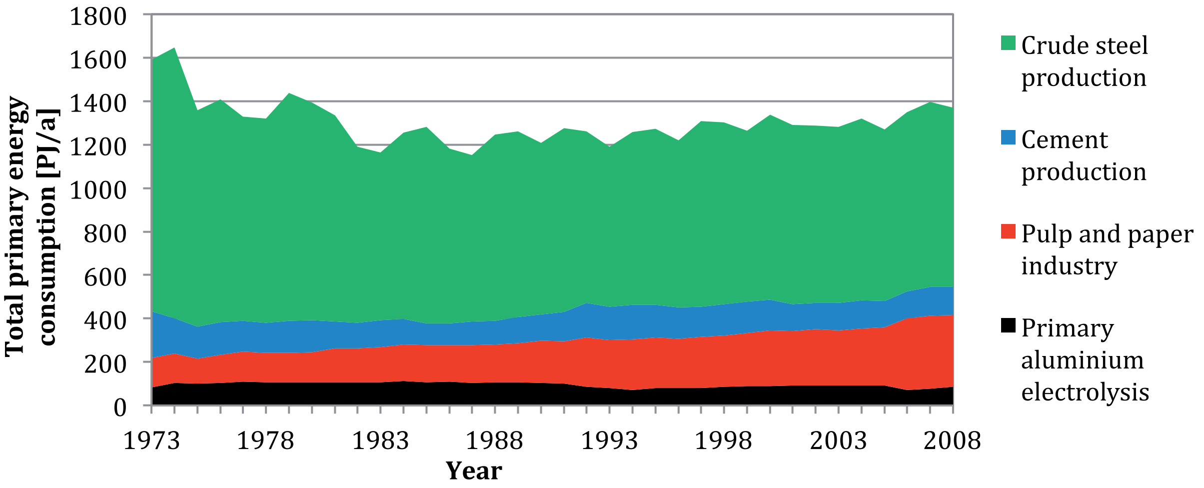

Figure 5. Development of the total primary energy consumption of the considered processes in Germany. The energy consumption of the clinker production process is included in the production process of cement.

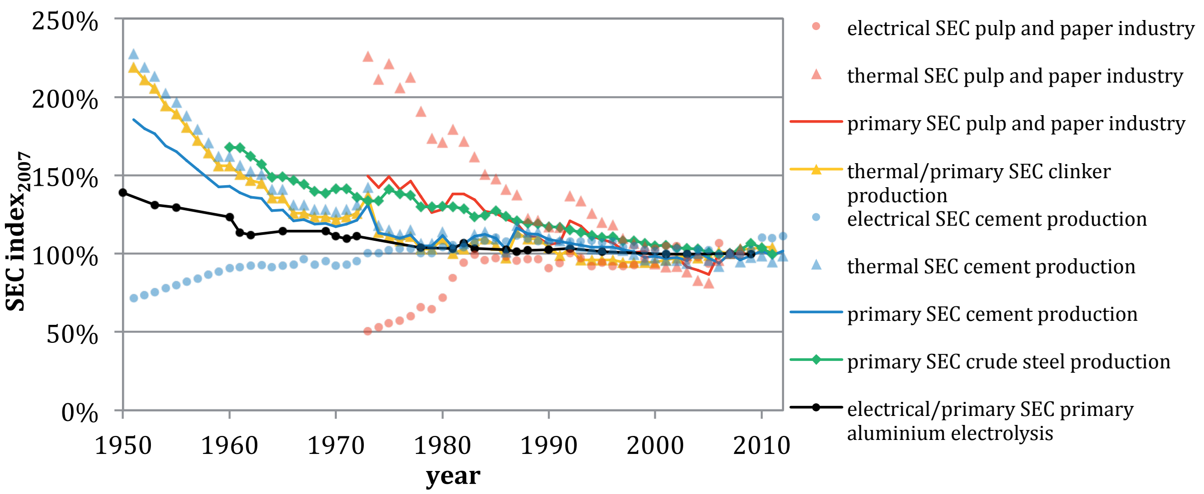

Figure 6. SEC over time. Dots, triangles and diamonds show the different types of SEC data which were introduced in the previous section. The lines represent the development of the primary SEC. The SEC of the year 2007 corresponds to 100 %.

SEC DATA BASIS

Figure 6 shows the data basis of the SEC relative to the base year 2007. It contains the data extracted from the data sources mentioned above including the necessary assumptions. In addition the calculated or approximated (see Table 6) primary SEC are presented.

The SEC has decreased in time for most cases except for the electrical SEC in the pulp and paper industry and the electrical SEC in the cement industry. The increase of electrical SEC in the pulp and paper industry is to a large extent a result of the introduction of new technologies that need more electricity but lead to much higher savings of thermal energy (see Götz 2007). In addition, demand for higher quality, especially on cement, as well as increasing automation and environmental requirements led to an increasing electrical SEC compared to thermal uses (see Löckener 2013, Götz 2007).

LEARNING CURVES AND RATES

The time evolution of the SECs is easy to read but the change in SEC with respect to growing cumulative production is closer to the learning curve approach. Accordingly, Figures 7–9 show the learning curves as a function of the cumulative production and are a direct input for the learning curve approach. To make the different industries comparable, the cumulative production has been indexed with respect to the year 2007.

Similar to Figure 6, we observe a decrease in SEC as a function of cumulative production for all sectors under consideration in Figure 7, except for the electrical SEC in the pulp and paper industry and in cement production. The reasons are the same as discussed for Figure 6. Also shown in Figure 7 are the fitted learning curves for the individual sectors and energy types. Some of the data reach back in time for more than five decades and yield both an informative relevant long-term perspective as well as a good input for the learning curve approach. As described above, the logarithm of the cumulative production and SEC has been taken to linearise the relationship between both quantities and to estimate learning rates. For closer inspection, Figure 8 shows the SEC as a function of cumulative production with logarithmic axes. The validity of the learning curve approach manifests itself in a linear dependence between SEC and cumulative production in this logarithmic presentation.

While Figures 7 and 8 displayed the researched data basis and the corresponding learning curves, Figure 9 shows the data and learning curves that were calculated and approximated as described at the end of the last section. Overall, we observe a good agreement between the linear learning curve fit and the empirical SEC and production data. The results of the statistical estimates for all data under consideration are summarised in the Table 7. Table 7 shows that all coefficients of determination are greater than or equal to 0.79. Thus, the learning curves are clearly correlated to the data series (see van Sark and Alsema 2006). The highest relative deviation between the learning rate and its standard error has been obtained for the primary energy consumption of the cement production. This is mainly due to the additional uncertainty resulting from the variation of the clinker factor. In general, the relative errors of the calculated LRs, $2\sigma_{LR}/LR$, are less than 22 %. Please note that all LRs as obtained from the available data are significantly different from zero (at 5 % confidence level as shown in Table 7, but also (not shown) at 1 % confidence level).

COMPARISON OF LEARNING RATES

Figure 10 shows the LRs obtained for the different sectors and energy types with their individual statistical uncertainties. The (negative) LRs for the increasing electrical SEC have been omitted.

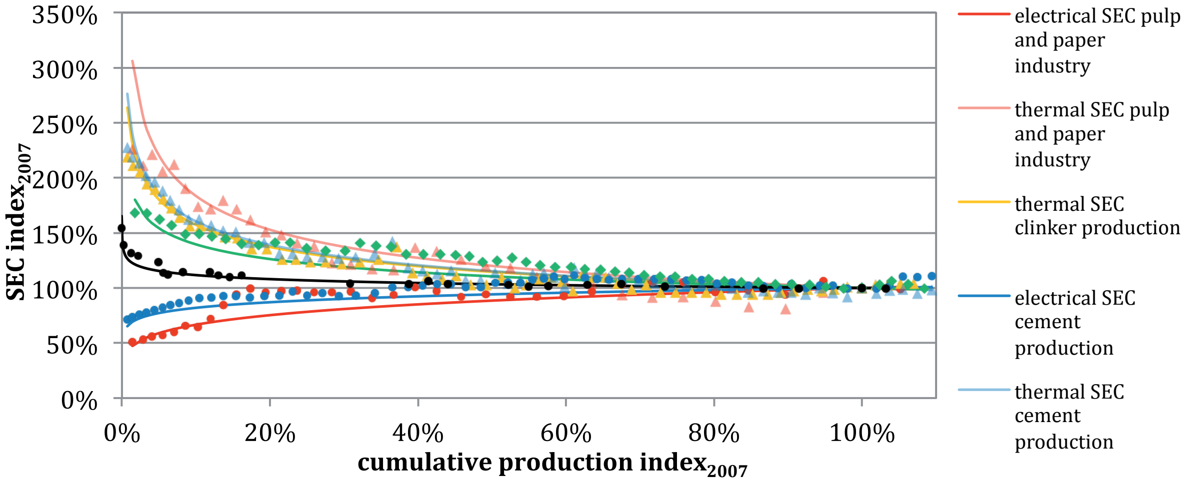

Figure 7. SEC over cumulative production. Dots, triangles and diamonds show the different types of SEC data points. The lines are the approximated learning curves. The approximated SEC and the cumulative production of the year 2007 correspond to 100 %.

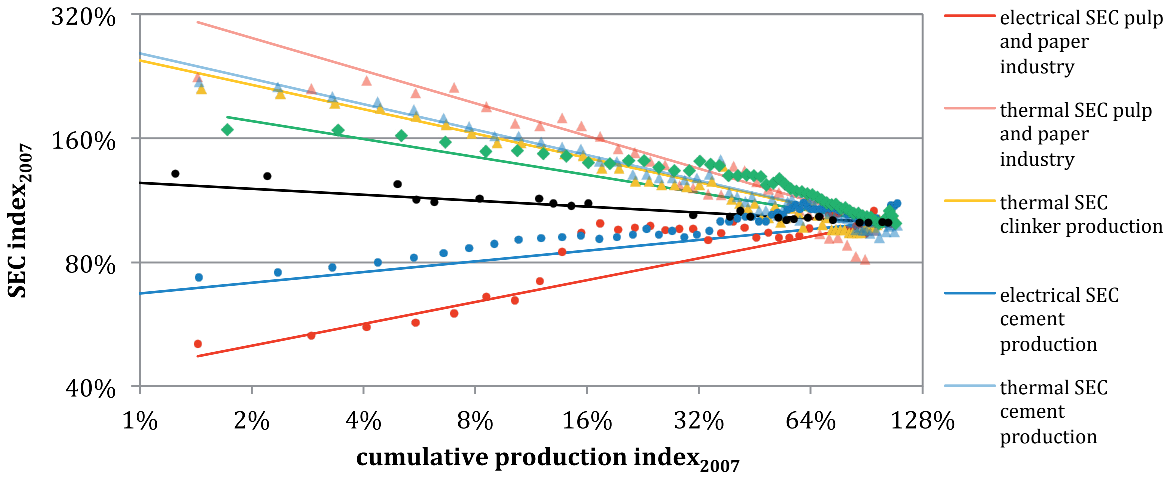

Figure 8. SEC over cumulative production, logarithmic display. Similar to Figure 7. Dots, triangles and diamonds show the different types of SEC data. The lines are the approximated learning curves. The approximated SEC and the cumulative production of the year 2007 correspond to 100 %.

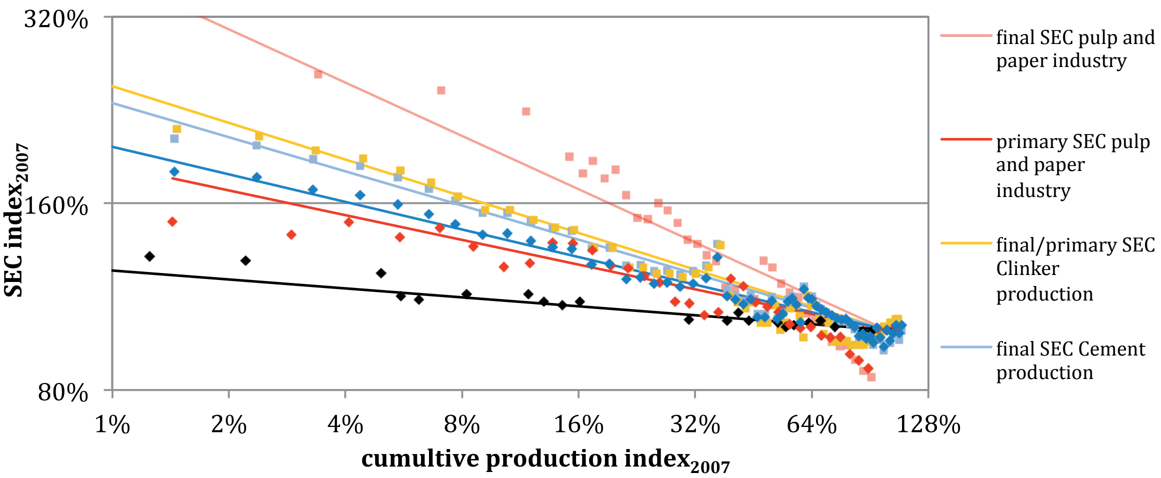

Figure 9. SEC over cumulative production, logarithmic display. Squares display final energy, diamonds final energy data points. In the cases of the clinker production and the primary aluminium electrolysis (where both energy types are represented by one line) we used the symbol of the energy type that leads to lower uncertainties in the approximation. The lines are the approximated learning curves. The approximated SEC and the cumulative production of the year 2007 correspond to 100 %.

Table 7. Statistical Results. LR, R^2 and the standard error. The LRs have been rounded to the nearest half of integer percentage. The statistical uncertainties $2\sigma_{LR}$ (or $2\sigma_{LR}$ + 1 % in the cases where the clinker factor was used for data preparation) have been rounded up to a half of integer percentage. LRs written in italic were obtained with assumptions based on the fact that the examined types of energy represent the dominant part of the final and primary energy. The statistical uncertainties of these LRs are qualitatively adapted.

Industry/product/process	Electricity		Thermal energy		Final energy		Primary energy	
	LR ± $2\sigma_{LR}$	R^2	LR ± $2\sigma_{LR}$	R^2	LR ± $2\sigma_{LR}$	R^2	LR ± $2\sigma_{LR}$	R^2
Pulp and paper industry*	-13.0 ± 2.0 %	0.79	16.5 ± 3.0 %	0.90	18.0 ± 3.5 %	0.86	9.0 ± 1.5 %	0.84
Clinker			12.5 ± 1.0 %	0.93	*12.5 ± 2.0 %*		*12.5 ± 3.0 %*	
Cement	-6.0 ± 1.0 %	0.85	13.5 ± 2.0 %	0.94	12.0 ± 2.0 %	0.94	9.5 ± 2.0 %	0.93
Crude steel							9.5 ± 1.5 %	0.80
Primary aluminium electrolysis	3.5 ± 0.5 %	0.93			*3.5 ± 1.0 %*		*3.5 ± 1.0 %*	

** The LR of the final energy of the pulp and paper industry does not match the other results of this industry because of the different time periods we used. A survey on the final SEC in the time period 1973–2008 leads to a LR of 13.5 ± 2.0 %. This problem will be treated more precisely in the methodical discussion.*

Figure 10 shows that higher aggregated data leads to a higher LR. This was expected since surveys on products and whole industries include developments in energy efficiency from more than efficiency improvements of processes. For example, the generation of electricity in power plants belonging to paper mills is within the system boundaries of our survey of this industry. In addition, the substitution of whole processes, products and raw materials are included, for example the increased recycling quota of paper and steel.

FORECAST OF SEC

Using the predicted production volumes of the study Fleiter et al. (2013), we made forecasts of the SEC in the years 2020 and 2035 by extrapolating the LRs. The results are shown in Table 8.

We compared these results to the different forecast scenarios by Fleiter et al. (2013). Fleiter et al. conducted a model-based bottom-up assessment of individual energy-efficiency measures in the energy-intensive processes and calculated energy saving potentials until 2020 and 2035. As expected our results show the highest agreement with the “business as usual” scenario of Fleiter et al. (2013). Most differences can be explained by different system boundaries. Furthermore, our results for the pulp and paper industry seem to be very optimistic. This can be explained by past improvements outside the production processes of the intermediate and the finished products, which are within the system boundaries of our analysis. The adoption of the shoe press was a leap in efficiency improvement, which cannot be expected to occur in the future (see Götz 2007, Fleiter et al. 2013). Our result shows that a forecast via the learning curve approach should be evaluated with a comparison between the technological development in the past and in the development that could be expected in future.

The weighted average of saving potentials leads to total savings of absolute primary energy consumption of 4.0 % between the

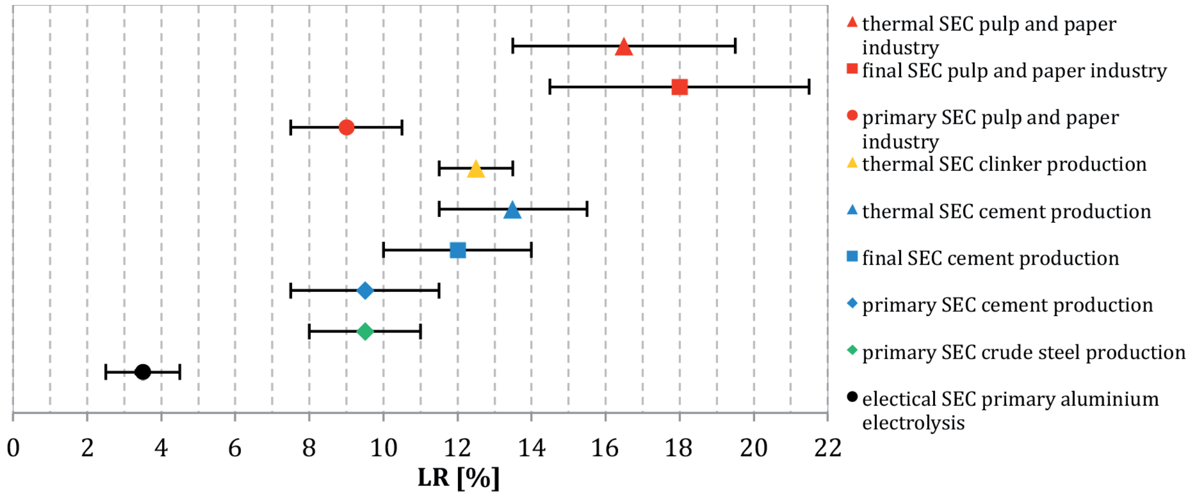

Figure 10. Summary of estimated LRs. The negative LRs of the electrical SEC of the pulp and paper industry and the production process of cement are not listed. Dots, triangles, diamonds and squares show the different types of energy. As already mentioned the LRs of the clinker production and the primary aluminium electrolyses can be adopted for final and primary energy as well, however the uncertainties increase.

Table 8. Forecast of the development of the SEC. This table shows the results of the trend extrapolation of the SECs and the percentage of savings.

Industry/product/process Energy form	2007 [GJ/t]	2020 [GJ/t]	2035 [GJ/t]	2020 [%]	2035 [%]
Pulp and paper industry					
Electrical energy	2.28	2.50	2.69	-9.75	-17.99
Thermal energy	7.63	6.64	5.96	12.99	21.91
Final energy	9.96	8.71	7.81	12.52	21.53
Primary energy	13.96	13.02	12.33	6.75	11.68
Clinker					
Thermal energy	3.51	3.38	3.26	3.91	7.25
Cement					
Electrical energy	0.39	0.39	0.40	-1.93	-3.75
Thermal energy	2.85	2.73	2.61	4.45	8.38
Final energy	3.23	3.10	2.98	3.97	7.51
Primary energy	3.97	3.85	3.73	3.22	6.11
Crude steel					
Primary energy	18.90	18.21	17.62	3.66	6.75
Primary aluminium electrolysis					
Electrical energy	46.92	46.47	46.03	0.97	1.91

years 2007 and 2020 and 6.9 % between the years 2007 and 2035 (the absolute primary energy consumptions of the year 2007 are used to calculate the weighted average across products).

Discussion and Conclusion

METHODICAL DISCUSSION

Our analysis has shown that the learning curve approach can be used to describe the long-term energy efficiency improvement in selected energy-intensive industries. For products and processes for which we were able to gather consistent data, we found a correlation between the increase in cumulative production and the energy efficiency improvement. Still, a few caveats need to be considered.

A well-known problem of the learning curve approach is the dependence on the time period that is covered by the input data. We examined the time period between 1955 and 2008 for the final SEC of the pulp and paper industry and obtained a LR of 18 %, while for the period between 1973 and 2008 the LR is 13.5 %. A possibility to estimate potential errors is to vary the time period examined and take time periods which are as long as possible to increase the number of data points.

As shown above, the learning curve regression and the data series are closely correlated. The largest deviations occur at the beginning of the analysed time period in some surveys (see Figures 7, 8 and 9). This phenomenon seems to occur systematically in surveys of highly aggregated data. The small number of analysed data sets in this study and the lack of comparable studies do not allow definite conclusions. Tests with synthetic data sets show that a linear decrease of the SEC over time leads to this phenomenon to a very marked degree. We assume that time-linear factors lead to this problem and prevent a higher goodness of fit. For example the stock turnover of production plants could be such a time-linear factor. According to Yeh and Rubin (2012), several studies find learning rates to be lower at the initial stage of technology diffusion than they would be when using the log-linear experience curve function.

The results of the forecast and the comparison with the study by Fleiter et al. (2013) have shown that the learning curve approach is a valid method to predict developments of the SEC in the future, in particular for business-as-usual scenarios. Here, the learning curve approach provides a reliable and rather easy-to-use method to obtain estimates for future energy consumptions. A technical overview of innovations in the past and predicted innovations for the future could help to decide whether the results of the forecast can be considered as optimistic or pessimistic.

The use of production data from Germany neglects the influence of technological learning taking place in other countries. While the production output of most considered products in Germany is relatively constant for the last few decades (see Figure 4), the worldwide output of these products has been increasing rapidly. On the other hand, worldwide production data ignores the specific situation in Germany, where for example the construction of new production plants is rare. Future research could use German and worldwide production data to take both the worldwide learning and the specific situation for Germany into account.

Overall, we find the learning curve approach as applied to specific energy consumption in energy-intense processes a simple and easy-to-use technique, which has so far only once been applied in a similar way (Ramirez and Worrell 2006). To arrive at definite quantitative conclusions about the learning rates in different processes and industries more data and studies from other countries as well as on other products and processes, such as ethylene, chlorine, ammonia, glass, or the individual types of steel, are needed.

POLICY CONCLUSIONS

From a policy perspective, the approach used allows to analyze the long term potentials for energy efficiency and energy savings in energy-intense industries. Despite high efficiency in many industries, the long-term view shows that an increase in efficiency is always possible. It is most dynamic in times of fast production output (and capacity) growth and slower in times of stagnating growth.

The policy-related interpretation, however, is not straight forward. Generally, the learning curve approach as used here seems to suggest that an increase in production should be aimed at since (within the learning curve logic) this will lead to reduced SEC. The fact that we use the cumulative production slightly softens this conclusion, as also a stagnating annual production will result in efficiency improvements, although on a lower level. Certainly, the exclusive explanation of efficiency improvements by production increases neglects other factors that also might have an impact. It particularly remains an open question, what the influence of policy instruments might be.

Further, we have some indication that the learning rates are increasing with broadening of system boundaries (from processes to products to industries). This indicates potentials for future improvements to be small in individual processes but noteworthy for whole product groups and industries. Thus, the results indicate that in order to achieve substantial energy savings in the long term, radically new process innovations or shifts between processes are required. Policies aiming at the development and market introduction of new processes as well as R&D can support these changes. Furthermore, energy efficiency goals should not be formulated for and individual process but for a whole industry. This would allow to lever larger savings potentials by shifts between different processes or a more integrated product process. As this observation is based on a limited data set follow-up studies looking at other processes, products and industries are certainly necessary.

References

BDZ, 2000. Zement-Jahresbericht 1999–2000. Düsseldorf: Bundesverband der Deutschen Zementindustrie, 2000.

de Beer, J.; Worrell, E.; Blok, K., 1998. Future technologies for energy-efficient iron and steel making. Annual Review of Energy and the Environment, 23 (1), pp. 123–205.

Briem, S.; Alkan, Z.; Quinkertz, R.; Dienhart, M.; Kugeler, K., 2000. Development of energy demand and energy-related CO_2 emissions in melt electrolysis for primary aluminium production. Aluminium 76 (6), pp. 502–506.

Chang, Y., Lee, J., & Yoon, H., 2012. Alternative projection of the world energy consumption-in comparison with the 2010 international energy outlook. Energy Policy, 50, pp. 154–160.

Crussard, C., 1978. A hundred years of aluminium electrolysis. Institution of Mining and Metallurgy Transactions 87 (6), pp. C146–C152.

Dienhart, M.: Ganzheitliche Bilanzierung der Energiebereitstellung für die Aluminiumherstellung. Aachen, 2003.

Erne, H., 1984. Die Bedeutung der Energie in der Sekundär-Aluminiumindustrie. Aluminium, 60 (3), pp. 231–233.

Fahrmeir, L., 2003. Statistik – Der Weg zur Datenanalyse. Berlin: Springer, 2003.

Fleiter, T.; Fehrenbach, D.; Worrell, E.; Eichhammer, W., 2012. Energy efficiency in the German pulp and paper industry – A model-based assessment of saving potentials. Energy, 40 (1), pp. 84–99.

Fleiter, T.; Schlomann, B.; Eichhammer, W. (eds.), 2013. Energieverbrauch und CO_2 Emissionen industrieller Prozesstechniken – Einsparpotenziale, Hemmnisse und Instrumente. Stuttgart: Fraunhofer Verlag.

Fleiter, T.; Schlomann, B.; Hirzel, S.; Arens, M.; Hassan, A.; Idrissova, F.; Reitze, F.; Toro, F.A.; Rohde, C.; Eichhammer, W.; Cebulla, F.; Jochem, E., 2011. Where are the promising energy-efficient technologies? A comprehensive analysis of the German energy-intensive industries: eceee summer study 2011, June 6–11, Presqu'île de Giens.

Franke, A., 1986: 100 Jahre industrielle Aluminium-Elektrolyse. Metall 40 (9), pp. 13–14.

Ginsberg, H., 1958. Stand der technischen Aluminium-Elektrolyse und sich abzeichnende Entwicklungsrichtungen. Metall 12 (3), p. 174.

Götz, B., 2007. Optimierung des Energieeinsatzes in der deutschen Papier- und Zellstoffindustrie. ipw – Das Papier 2007 (12), pp. 43–48.

Hettinga, W. G.; Junginger, H. M.; Dekker, S. C.; Hoogwijk, M.; McAloon, A. J.; Hicks, K. B., 2009. Understanding the reductions in US corn ethanol production costs – An experience curve approach. Energy Policy 37 (1), pp. 190–203.

Hasanbeigi, A.; Menke, C.; Therdyothin, A., 2010. The use of conservation supply curves in energy policy and economic analysis: the case study of Thai cement industry. Energy Policy, 38 (1), pp. 392–405.

IEA, 2000. Experience Curves for Energy Technology Policy, International Energy Agency (IEA) (ed.), Paris: OECD/IEA.

IPPC, 2001. Reference Document on Best Available Techniques in the Non Ferrous Metals Industries. Integrated Pollution Prevention and Control, 2001.

IPPC, 2009. Draft Reference Document on Best Available Techniques in the Non Ferrous Metals Industries. Integrated Pollution Prevention and Control, 2009.

Jakob, M.; Madlener, R., 2004. Riding down the experience curve for energy efficient building envelopes: the Swiss case for 1970 to 2020. International Journal Energy Technology and Policy, 2 (1), pp. 153–178.

Jardot, D., Eichhammer, W., & Fleiter, T., 2010. Effects of economies of scale and experience on the costs of energy-efficient technologies – case study of electric motors in Germany. Energy Efficiency, 3 (4), pp. 331–346.

Kammer, C., 2011. Aluminium Taschenbuch – Band 1: Grundlagen und Werkstoffe. Berlin: Beuth, 2011.

Klaasen, G.; Miketa, A.; Larsen, K.; Sundqvist, T., 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. In: Ecological Economics 54 (2–3), pp. 227–240.

Krone, K., 2000. Aluminiumrecycling. Berlin: Beuth, 2000.

Lesclous, R.; Fridenson, P., 1999. Histoire des sites producteurs d'aluminium – Les choix stratégiques de Péchiney, 1892–1992. Paris: Presses de l'Ecole des Mines, 1999.

Löckener, R., 2013. Nachhaltigkeit und Zementindustrie – Dokumentation von Beiträgen und Handlungsoptionen. Verein Deutscher Zementhersteller, 2013.

Neij, L., 2008. Cost development of future technologies for power generation – A study based on experience curves and complementary bottom-up assessments. Energy Policy 36 (6), pp. 2200–2211.

Pardo, N.; Moya, J. A., 2013. Prospective scenarios on energy efficiency and CO_2 emissions in the European Iron & Steel industry. Energy.

Pardo, N.; Moya, J.A.; Mercier, A., 2011. Prospective on the energy efficiency and CO_2 emissions in the EU cement industry. Energy, 36 (5), pp. 3244–3254.

Quinkertz, R., 2002. Optimierung der Energienutzung bei der Aluminiumherstellung. Aachen: 2002.

Ramírez, C. A.; Worrell, E., 2006. Feeding fossil fuels to the soil. Resources, Conservation and Recycling 46 (1), pp. 75–93.

Saygin, D.; Worrell, E.; Patel, M.K.; Gielen, D.J., 2011. Benchmarking the energy use of energy-intensive industries in industrialized and in developing countries. Energy, 36 (11), pp. 6661–6673.

Schall, D., & Hirzel, S., 2012. Thermal cooling using low-temperature waste heat: a cost-effective way for industrial companies to improve energy efficiency? Energy Efficiency, 5 (4), pp. 547–569.

Schmitt, H., 1961. Neue Gesichtspunkte beim Bau von Aluminium-Elektrolyseöfen. Erzmetall 14 (9), pp. 455–457.

Schwarz, H.-G., 2008. Technology diffusion in metal industries – driving forces and barriers in the German aluminium smelting sector. Journal of Cleaner Production 16 (1), pp. 37–49.

Taylor und Fujita Taylor, M.; Fujita, S.: Accounting for innovation in energy efficiency regulation. In: eceee 2013 Summer Study proceedings, S. 601–612.

Van Sark, W., 2008. Introducing errors in progress ratios determined from experience curves. Technological Forecasting and Social Change 75 (3), pp. 405–415.

Van Sark, W.; Alsema, E. A., 2006. Potential errors when fitting experience curves by means of spreadsheet software. Energy Policy 38 (11), pp. 7508–7511.

VDP, various years of publication. Ein Leistungsbericht, Bonn: Verein Deutscher Papierfabriken.

VDZ, 2011. Umweltdaten der deutschen Zementindustrie. Düsseldorf: Verein Deutscher Zementhersteller, 2011.

VDZ, 2013a. data sheet of production an SEC of clinker and cement, Düsseldorf: Verein Deutscher Zementhersteller, 2013, personal communication.

VDZ, 2013b. Monitoring-Abschlussbericht 1990–2012 – Verminderung der CO_2-Emmissiopnen, Beitrag der deutschen Zementindustrie. Düsseldorf: Verein Deutscher Zementhersteller, 2013.

WBMS, different years of publication. Metallstatistik. Herdfortshire: Ware.

Weiss, M.; Patel, M.; Junginger, M.; Blok, K., 2010a. Analyzing price and efficiency dynamics of large appliances with the experience curve approach. Energy Policy 38 (2), pp. 770–783.

Weiss, M., Junginger, M., Patel, M. K., & Blok, K., 2010b. A review of experience curve analyses for energy demand technologies. Technological forecasting and social change, 77 (3), pp. 411–428.

Werner, H., 1978. Entwicklung und Stand der Aluminiumerzeugung. Neue Hütte 23 (3), pp. 77–81.

Winkhaus, G., 1981. Herausforderungen an die Verfahrenstechnik der Aluminiumoxidherstellung. Aluminium 57 (10), p. 65.

Worrell, E.; Martin, N.; Price, L., 2000. Potentials for energy efficiency improvement in the US cement industry. Energy, 25 (12), pp. 1189–1214.

Worrell, E.; Neelis, M.; Price, L.; Galitsky, C.; Nan, Z., 2007. World Best Practice Energy Intensity Values for Selected Industrial Sectors.

WV-Stahl, various years of publication. Statistisches Jahrbuch der Stahlindustrie. Düsseldorf: Stahleisen-Verlag.

Yeh, S., Rubin, E., 2012. A review of uncertainties in technology experience curves. Energy Economics, 34 (3), pp. 762–771.