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Learning curves for solid oxide fuel cells

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ABSTRACT

In this article we present learning curves for solid oxide fuel cells (SOFCs). With data from fuel cell manufacturers we derive a detailed breakdown of their production costs. We develop a bottom-up model that allows for determining overall SOFC manufacturing costs with their respective cost components, among which material, energy, labor and capital charges. The results obtained from our model prove to deviate by at most 13% from total cost figures quoted in the literature. For the R&D stage of development and diffusion, we find local learning rates between 13% and 17% and we demonstrate that the corresponding cost reductions result essentially from learning-by-searching effects. When considering periods in time that focus on the pilot and early commercial production stages, we find regional learning rates of 27% and 1%, respectively, which we assume derive mainly from genuine learning phenomena. These figures turnout significantly higher, approximately 44% and 12% respectively, if also effects of economies-of-scale and automation are included. When combining all production stages we obtain *lr* = 35%, which represents a mix of cost reduction phenomena. This high learning rate value and the potential to scale up production suggest that continued efforts in the development of SOFC manufacturing processes, as well as deployment and use of SOFCs, may lead to substantial further cost reductions.

1. Introduction

Interest in power generation with solid oxide fuel cells (SOFCs), as well as R&D dedicated to this type of technology, has considerably increased over the past few years. Among the reasons are their high net electrical efficiency, in Alternative Current (AC), relative to conventional gas and coal based power units: even in comparison to for instance an integrated gasification combined cycle (IGCC) plant their efficiency is typically more than 10% higher [1]. Another explanation for the increased attention for SOFCs is the possibility of effectively recovering their exhaust heat, given the high temperatures under which they operate. As with other fuel cell systems, a combined heat and power (CHP) SOFC system consists of a stack of SOFCs and a balance-of-plant (BoP). The electrochemical reaction between oxygen and the fuel – such as hydrogen or a hydrocarbon gas like methane – takes place in the stack of fuel cells. The BoP supports the stack, drives the fuel and oxidant (i.e. air) to the fuel cells and can recover energy from the high-temperature exhaust gas. Main disadvantages of SOFC technology are the inabilities to rapidly start operation, switch off and to respond to unexpected variations in power demand.

Whereas their electric efficiency and ensuing economic benefits may be high, the fabrication costs of SOFCs and their resulting CHP systems, hence their purchase prices, are still significantly higher than strategically adopted target values. As a result, the cost of electricity generation with SOFCs are today well above those of most conventional alternatives. The development of SOFCs, however, is in the transition step between pilot and very early commercial stages and has not yet reached large commercial production. Progressively significant cost reductions are expected for the future when the technology transits through the various stages of maturation, as a result of likely improvements in the fabrication process, a probable enhancement of its performance by technical progress and the acquisition of experience at the stages of both manufacturing and commercialization. Learning is defined as the cumulative effect of each of the previously mentioned factors that generate stocks of knowledge, experience, (physical or institutional) infrastructures and skills. The impact of learning on manufacturing costs is usually expressed by the learning rate, a measure for the relative cost decrease of a technology with every doubling of produced or installed capacity. The representation of costs versus cumulative capacity or production of a technology results in a learning curve that in principle could allow for estimating the cost prospects of innovative technology and for determining the competitive breakeven point with respect to existing technology.

Schoots et al. [2] present an extensive analysis of global learning phenomena for several fuel cell technologies: proton exchange

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membrane fuel cells (PEMFCs), phosphoric acid fuel cells (PAFCs) and alkaline fuel cells (AFCs). The present work complements this recent fuel cell learning curve study, since so far no learning rates have been reported – or have been determined – for SOFCs. To our knowledge only Krewitt and Schmid [3] have attempted to determine a learning curve for SOFCs, but they found that insufficient information on produced SOFC capacity was available at the time to calculate a learning rate. Hence, their preliminary findings remained unpublished. We here report for the first time a reliable learning curve for SOFCs and describe how we performed our corresponding analysis. Apart from the fact that we studied a different type of fuel cell, our work distinguishes itself from the analysis reported in Schoots et al. [2] in that we obtained sufficient data from manufacturing facilities with enough detail to allow us to disentangle and measure the impact of learning on cost reductions at different stages of the fuel cell development process.

In Section 2 of this article we briefly recapitulate the general concept behind learning curves and explain how one calculates a learning rate. In Section 3 we present our study of SOFC costs and the effects of phenomena such as fuel cell production automation and economies-of-scale; we also describe in detail the cost model that we use for our analysis and the roles played herein by material, energy, labor and capital charges. On the basis of both literature and modeled data we determine learning curves for SOFCs in Section 4. In Section 5 we discuss our assumptions and evaluate the calculated learning rates in a broader perspective, in particular by unpacking the SOFC learning curves by production stage and cost reduction mechanism. We summarize our main conclusions in Section 6.

2. Learning curves

Since the development of the first learning curve for the aircraft industry in 1936 [4], many technologies have been subjected to learning curve studies, as a means to evaluate potential cost reductions based on realized progress in the past. Learning curves have been determined for a large range of different types of technologies and may serve company strategic purposes and as a tool for public policy making. Well known are learning curves for energy-related technologies, such as coal-burning power units [5], gas turbines [6], wind turbines [7] and photovoltaic modules [8]. A learning curve expresses graphically the cost decrease of a technology as function of cumulative production. The most common type of equation to correlate cost and cumulative production values in this area is a power law (see Eq. (1)). When cost and cumulative capacity data are represented in logarithmic form, the power law of a learning curve becomes a downward sloping straight line. The slope of this line is called the learning index (α) [9,10], which can be reformulated as the learning rate (lr) (see Eq. (2)). The latter expresses, usually in percentages, the relative cost reduction after each doubling of cumulatively produced items of a technology. The learning rate provides a quantitative measurement of the effect of (the aggregation of) various cost reduction drivers, among them in particular (but not necessarily exclusively) economies-of-scale and 'true' learning. The latter may originate from (1) the accumulated knowledge regarding the technological principles or the production and marketing processes of the technology and/or (2) implemented improvements in the overall infrastructure needed for the technology manufacturing procedure. In our case of fuel cells, the variables in Eq. (1) are the costs of SOFCs at time t (c_t), the costs of SOFCs in the time set as reference and referred to as $t = 0$ (c_0), the cumulated production of SOFCs at time t (P_t) and the total number of SOFCs produced until the time set as reference (hence at $t = 0$) (P_0). We express values of P either in number of SOFCs (typically for fuel cells) or in terms of their capacity (hence in kW, for example when referring to SOFC systems).

$$c_t = c_0 \left(\frac{P_t}{P_0} \right)^{-\alpha} \tag{1}$$

$$lr = 1 - 2^{-\alpha} \tag{2}$$

A learning rate summarizes how cost reductions materialize when a manufacturer accumulates production or, alternatively, when it contributes to cumulative production of a technology thereby adding to the (global, regional or local) experience stock [11]. According to Lindman and Söderholm [11], learning is often not a public good, hence factors like the regional context, deployment and R&D support influence the cost reductions realized for a technology. The latter could be expressed by more complex mathematical learning curve expressions. Limited availability of data, however, prevents us from using more complex learning curve expressions than the one employed for this paper. In practice it proves difficult to distinguish between different cost reduction sources, as in our case with SOFC technology: the production process typically improves through several distinct ways, not only by the acquisition of experience based on manufacturing and deployment (learning-by-doing) but also via R&D efforts (learning-by-searching), and quite possibly from still other mechanisms such as technology spillovers [11–16]. Additionally to learning phenomena, effects of economies-of-scale, automation and market prices of raw materials eventually may contribute to costs reductions. Conventionally and erroneously these last elements are seen as part of learning, even though they are externalities not directly linked to a specific technology. Hence, in this work major efforts target to clarify the cost reduction of SOFCs by means of learning and non learning phenomena. It is conventional wisdom, and common practice in most studies, that learning rates are determined for technologies that have matured sufficiently and have reached advanced stages of commercial deployment – presently not yet the case for SOFCs – so that they mostly capture the effect of learning-by-doing. According to Ferioli and van der Zwaan [17], however, learning curves often apply only up to and including the early phase of commercial deployment. In those cases, as they argue, learning curves usually reflect several types of cost reductions, e.g. as associated with both learning-by-doing and learning-by-searching. Their observation, plus the asserted transition towards early commercial production of SOFCs over recent years, motivated our attempt to develop a learning curve for SOFC technology. Learning curve analysis can provide valuable insights for strategic planning and policy making, and can help determining or shaping indicators like total investment requirements and needs for financial support or deployment levels at which new energy technologies such as SOFCs become competitive with incumbent technologies.

3. Cost requirements for SOFCs

Since SOFC systems operate at temperatures above 900 K and present relatively long start-up times, they are principally considered for stationary and micro-stationary CHP generation purposes. Some specific mobile market applications exist, for example as auxiliary power supplies (APUs) in trucks. Apart from their high electric efficiency, other benefits are that they may be designed in a variety of distinct forms and set-ups, and can run on different types of fuel [18–20]. In the current early commercial production phase, planar and tubular geometries of SOFCs dominate triangular and other shapes. For all these geometries, individual fuel cells are assembled in stacks (planar) or modules (tubular) that are subsequently integrated with the BoP. An individual fuel cell consists of a multilayer device including the anode, electrolyte, cathode and interconnects. For an SOFC, the first three components are made of ceramics, such as respectively Nickel Oxide–Yttria Stabilized Zirconia (NiO–YSZ),

YSZ and Lanthanum Strontium Manganite (LSM). Interconnects are typically fabricated of stainless steel alloys [21–24]. In each of the three layers the use of other materials is being experimented with as aim to realize potential fuel cell performance improvements. Today, NiO, YSZ and LSM constitute the state-of-the-art raw materials needed and are employed for the production of the vast majority of SOFCs. They are therefore the focus of the present study. We will mostly investigate planar SOFCs, because data for this type are more abundant than for tubular SOFCs. An analysis of the manufacturing sequence and cost components of SOFC production, as described in the following sections, serves to estimate total fuel cell and system fabrication costs. The latter constitute the basis for our attempt to determine a learning curve for SOFCs.

3.1. Total costs

For planar SOFC fabrication, units of the desired size are cut from long sheets of multilayered ceramics. These units are commonly shaped in rectangular or circular form. The sheets are produced according to a specific sequence of steps and techniques that depend on (and determine) the manufacturing material, processing speed, production yield and production cost. The thickest layer usually defines which of the three acts as the mechanical support of the fuel cell: anode, electrolyte or cathode. The other two components are deposited as coatings. For anode-supported SOFCs, currently the most widely adopted fuel cell type, the production process starts with tape-casting a slurry of NiO–YSZ, organic binder and solvents, followed by drying the resulting sheets in order to get a relatively thick and flexible foil. This thick, relatively coarsely structured component has limited catalytic (electrochemical) activity and mainly provides mechanical support and electronic conductivity. A thin layer of approximately the same NiO–YSZ composition but with a fine microstructure is added by spraying, tape-casting or screen-printing this material atop. This finely structured layer, sometimes called the anode functional layer (AFL), generates the main catalytic activity for the fuel oxidation. On top of the AFL a thin YSZ layer is deposited with similar processes as the AFL. This assembly is co-sintered at a temperature well above 1500 K. The cathode layer is added by screen-printing or spraying LSM-YSZ onto the electrolyte, after which the total assembly is sintered again, this time at a lower temperature [25–27]. After the cutting process, elementary fuel cells are formed by adding shaped interconnects to the multilayered ceramic units. A series of individual elementary fuel cells are piled together to become a SOFC stack. For other kinds of fuel cell support – that is, cathode or electrolyte based – similar manufacturing techniques are used. For our planar SOFC study we assess the most commonly used method for multilayered ceramics manufacturing, which is the tape-casting of the anode-support, and screen-printing of the anode functional layer, electrolyte and cathode.

Most intricacies of SOFC manufacturing techniques and materials are well documented in the literature. Often lacking or poorly explained, however, are data on overall SOFC production cost. While cost components related to the use of materials and energy are usually fairly well known, little information is often available on contributions from notably labor and capital charges. This implies that total manufacturing cost values quoted in public sources possess a high degree of heterogeneity. In general substantial uncertainty exists regarding the precise content of these cost figures. This complicates attempts to observe learning phenomena, and renders difficult efforts to accurately calculate learning rates. In order to determine the presence (or absence) of learning-by-doing, and develop learning curves, cost data should obviously be as homogeneous and inter-comparable as possible. We have therefore greatly endeavored to subtract heterogeneity from our data set as much as possible. For this purpose we developed a detailed bottom-up model in which we distinguish between the four main cost components that contribute to the overall SOFC production process:

- Material costs.
- Energy costs.
- Labor costs.
- Capital charges.

To our knowledge, the consulting firm Arthur D. Little has been the first to present a detailed production cost breakdown for planar anode-supported SOFC systems [28]. The fuel cells studied in [28] use gasoline or diesel as fuel, reach a power density between 0.3 and 0.6 W/cm^2 and have an active area of 100 cm^2. Total costs are estimated at 4–6 $(2001) per elementary fuel cell, that is, between 102 and 253 $(2001)/kW. These numbers include cost components for stack end-plates, current collectors, electrical and thermal insulators, sensors and assembling. Woodward also presents a detailed model for overall SOFC fabrication costs, which includes the costs for the production of ceramics, manufacturing and equipment charges, as well as expenses associated with production yield and performance testing [25]. The assumptions regarding equipment costs, however, are not clearly specified. Manufacturing costs for production volumes reaching 500,000 fuel cells per year are estimated at about 7 $(2003) per elementary fuel cell, or 88 $(2003)/kW. Koslowske describes a model similar to that of Woodward, and estimates a cost of approximately 3 $(2003) per elementary fuel cell, or 56 $(2003)/kW, for a production volume of 5 million fuel cells per year [29]. Last two mentioned works do not precise interconnects costs. The information presented in these three publications is certainly interesting, but large differences between their results are apparent. These discrepancies result not only from varying assumptions regarding included cost components, but also from important economies-of-scale effects. The findings by Koslowske should be valued with caution, since today fuel cell production per manufacturer takes place at levels well below the scale assumed. The maximum manufacturing rate attained so far is approximately 500,000 fuel cells annually. Any cost reduction claims for higher production scales still need to be confirmed.

As demonstrated by a comparison of these three studies, fuel cell production costs heavily depend on the production volume, hence a large potential exists for economies-of-scale. Many of the differences observed in the literature for overall fuel cell manufacturing costs, as well as the contributions hereto from different cost components, can be explained by economies-of-scale effects. A publication by Thijssen [30] proffers an extensive study of the influence of high production volumes on fuel cell manufacturing costs. From the numbers provided in this study and the results that follow from our cost model, we conclude that fuel cell manufacturing costs at large production volumes can be significantly lower than at low volumes. The main reason is that capital investments are more economically exploited in the former case. For material, energy and labor costs similar savings may hold, although less pronounced than with capital charges. Because the capital charges per fuel cell decrease so rapidly with the production scale during the early pilot stage, also their relative contribution to fuel cell manufacturing costs falls. Consequently, the relative (but not the absolute) contributions from the other cost components increase during this early phase of fuel cell development (see the insert of Fig. 1). Labor cost takes the lead until setting process automation. At full commercial production, however, the relative contribution of capital charges strongly increases, while the relative contribution from labor drops mainly due to the automation of the production process (see Fig. 1).

Fig. 1 graphically describes how, as the production scale of fuel cells increases, labor costs progressively take the lead until the

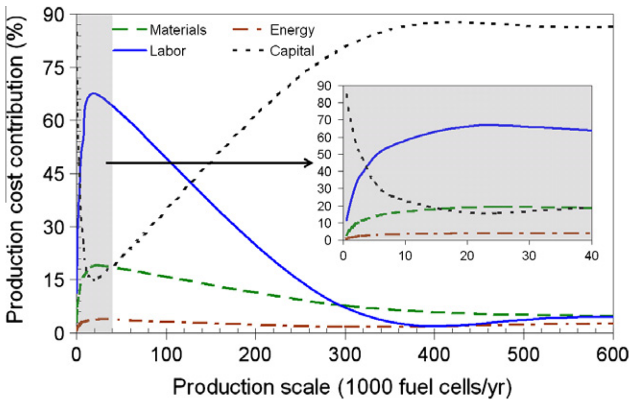

Fig. 1. Relative contributions from the four main components of total SOFC fabrication costs as function of the production scale, from the early pilot phase to full commercial development. Data from our model and Thijssen [30].

impact of automation kicks in. At large production volumes, SOFC production costs can be significantly driven down by focusing on automating the manufacturing process. Other cost improvements can result from the high volume purchase of ceramics. Our question now is whether, in addition to economies-of-scale and automation effects, cost reductions through learning phenomena exist and, if so, whether they can be observed. To answer this question we need to understand how each of the complementary cost reduction phenomena affects the production process, and whether these different effects can be disentangled. While the main goal of this paper is to study all factors that may lead to SOFC production cost reductions, we are particularly interested in distinguishing learning effects from the consequences of economies-of-scale and automation.

3.2. Cost components

In order to effectively compare the results from our model with data reported in the literature, we evaluate two different expressions for total SOFC manufacturing costs:

- The sum of material, energy and labor costs.
- The sum of material, energy, labor and capital costs.

We integrate the respective cost components by adding their total annual values for the production facility under consideration. The latter reminds that costs obtained and homogenized are manufacturer based. By dividing the resulting total annual manufacturing costs ($\sum C_i$) by the number of fuel cells produced every year (N_{fc}), we obtain the fuel cell production cost (C_{fc}, see Eq. (3)). Likewise, by dividing the total annual manufacturing costs by the total capacity produced every year, we obtain the fuel cell capacity cost ($C_{K,fc}$, see Eq. (4)). The total annual capacity is obtained by multiplying N_{fc} by the fuel cell power density (W_{fc}) and its active area (A_{fc}), expressed in kW/m^2 and m^2 respectively.

$$C_{fc} = \frac{\sum C_i}{N_{fc}} \tag{3}$$

$$C_{K,fc} = \frac{\sum C_i}{N_{fc} \times W_{fc} \times A_{fc}} \tag{4}$$

The drawback of Eq. (3) is that the SOFC surface and stack height (hence capacity) vary significantly between manufacturers, so that cost figures are often hard to compare. Eq. (4) on the other hand renders quotes from different sources and facilities more comparable, by expressing costs per unit of produced capacity. The latter are usually referred to as the specific costs. In this paper we use cost data from 1996 to 2008, which we correct for country-specific inflation and exchange rates within the concerned period to obtain costs expressed in \$(2008) – this increases comparability [31–33]. Depending on the year considered in this time frame, we also account for differences in salaries [34] and energy costs depending on the country in which the fuel cell production plant operates [35,36]. We apply these respective correction factors to ensure that all modeling results and literature data for specific costs are mutually as consistent as possible. We normalize cost data for reasons of industrial confidentiality.

3.2.1. Material costs

For a manufacturing facility the total annual material costs (C_{mat}) are obtained by summing the products of the annually purchased material volumes ($m_{NiO-YSZ}, m_{YSZ}, m_{LSM}, m_{int}$) and their respective costs per kg ($c_{NiO-YSZ}, c_{YSZ}, c_{LSM}, c_{int}$), with the subscript *int* referring to the interconnects:

$$C_{mat} = c_{NiO-YSZ} \times m_{NiO-YSZ} + c_{YSZ} \times m_{YSZ} + c_{LSM} \times m_{LSM} + c_{int} \times m_{int} \tag{5}$$

When a production facility expands, the volume of materials that needs to be processed increases accordingly. Obtaining the necessary high granularity (that is, small particle size) of the input powders is a costly procedure at small volumes, but becomes exceedingly cheap at large quantities (and is then typically dealt with within the SOFC production facility). Consequently, material costs can be driven down to essentially the costs of raw materials by increasing the production scale sufficiently. Costs for powder granularisation remain often unknown, probably because their contribution to total material costs becomes insignificant when large volumes of SOFCs are manufactured. For a volume of NiO–YSZ lower than 100 kg its price may be as high as 100–200 \$(2008)/kg [37]. This price can decrease, however, to a level as low as 15 \$(2008)/kg for manufacturing volumes that are at least an order of magnitude larger [38]. For YSZ and LSM the material costs for high purchase volumes reach values of typically 13 \$(2008)/kg and 26 \$(2008)/kg, respectively [39,40].

Since the costs of NiO–YSZ and YSZ powders are almost the same, we assume that they also vary similarly in proportion to their purchase volumes. We assume that LSM is consistently two times more costly than YSZ, so that these two substances follow the same dependency on the annually purchased volume of material, based on cost values presented in [38]. For all required substances we suppose that their costs at high volume consumption levels are constrained to values slightly above the corresponding raw material costs, to which thus no further cost reductions apply [40]. The total amount purchased of each powder is estimated on the basis of the density and thickness of each sintered layer [41–44], as well as the surface and number of SOFCs produced annually. Fig. 2 shows the costs per kg of NiO–YSZ powder for different consumption volumes, as well as our fit of the data points with a logarithmic equation. The result of our logarithmic regression is:

$$c_{NiO-YSZ} = -6.4565 \times \ln(m_{NiO-YSZ}) + 66.553 \tag{6}$$

For fabricating fuel cell interconnects SOFC manufacturers usually buy pre-formed thick plates of special stainless steel alloys, for which on the basis of market prices we assume a constant cost charge of 275 \$(2008)/kg. We neglect steel price fluctuations, and assume that the variability of stainless steel prices, due to the sizeable diversity of alloys on offer as well as high market volatility, outweigh possible scaling effects.

3.2.2. Energy costs

The energy input contribution to total SOFC fabrication costs cannot be neglected. We assume that the total annual energy

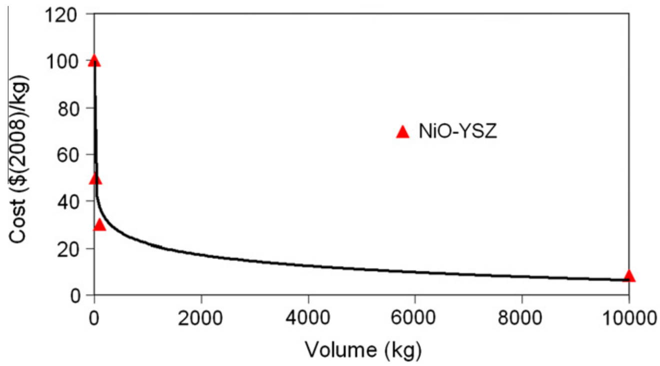

Fig. 2. Cost of NiO–YSZ powder per kg as function of volume purchased.

expenses (C_{en}) of an SOFC production facility result from three factors, that is, the total fuel cell capacity produced by the facility per year, the energy requirements per unit of capacity and the costs of energy:

$$C_{en} = N_{fc} \times W_{fc} \times A_{fc} \times (c_{el,kWh} E_{el}) \tag{7}$$

In Eq. (7), $N_{fc} \times W_{fc} \times A_{fc}$ represents again the total SOFC capacity annually produced, while the factor between brackets constitutes the energy costs incurred per unit of fabricated capacity expressed in kW. We assume that essentially electric energy (E_{el}) is consumed during the manufacturing process of fuel cells, which in this case is usually expressed in kWh/kW. Multiplying E_{el} by the kWh electricity price ($c_{el,kWh}$), expressed in \$(2008)/kWh, yields the energy cost component per kW of fabricated SOFCs [45]. Because of lack of precise data, we assume electricity cost values that are an average between private and industrial prices as applied to the country under consideration and the point in time at which the fuel cells are manufactured. Eq. (7) ascertains that the energy component of total SOFC manufacturing costs is appropriately homogenized and averaged over a year's worth of fuel cell production activity by a given plant.

3.2.3. Labor costs

Especially in the early phase of fuel cell fabrication, labor constitutes one of the most important cost components of the overall production process. For the annual level of labor expenses (C_{lab}) we only consider direct costs, that is, labor as related to the operation of the SOFC production facility. We do not include secondary labor for powder preparation, because we consider these cost components either insufficiently relevant for our SOFC manufacturing cost analysis or think that they are already accounted for indirectly (as with their inclusion for instance in the prices of materials). Data from ECN and several manufacturers show that, when no process automation techniques are implemented, the work directly related to SOFC manufacturing and stack assembling is performed by typically five individuals (full-time employed) when an annual volume of 25,000 fuel cells is produced [27,46]. We assume that C_{lab} is proportional to the gross Average Employment Income (*AEI*) in the country under consideration [34] and that, with no automation, the number of individuals employed in the plant increases linearly with the production scale:

$$C_{\mathrm{lab}} = AEI\left(N_{fc}\frac{5}{25{,}000}\right)^{\beta} \tag{8}$$

Eq. (8) is represented as a power law to account for the possibility of automation. In the case of non-automation we assume $\beta = 1.0$, so that the number of persons at work varies in proportion to the annual fuel cell production level. In order to allow for automation effects we suppose that Eq. (8) becomes non-linear, with typically $0.2 < \beta < 1.0$. On the basis of expert elicitation, we confirm that our default assumption of linearity between the number of individuals employed and the annual number of fuel cells produced constitutes a good approximation. The use of the AEI index has as double advantage that it reduces the influence of wage differences between technical workers and administrative personnel, and avoids the need for determining precisely how many employees in each of these professional categories are involved in the production process.

3.2.4. Capital costs

Two main types of capital charges can be distinguished for the construction of a fuel cell production facility: equipment costs (C_{eq}) and terrain plus building costs (C_{tr}). Both C_{eq} and C_{tr} represent total cost figures – in order to obtain the overall capital cost expenses per annum (C_{cap}), these cost figures are transformed from total investment requirements to annual capital costs, through the annuities relationship for capital refunding, and then summed:

$$C_{\mathrm{cap}} = C_{eq}\left[\frac{r}{1-(1+r)^{-T}}\right] + C_{tr}\left[\frac{r}{1-(1+r)^{-T}}\right] \tag{9}$$

In Eq. (9), r is the real interest rate (which we suppose to be 8%) and T the period of loan amortization (for which we assume a time frame of 10 years). For building an SOFC manufacturing plant the equipment cost term (C_{eq}) in Eq. (9) is dominated by the purchase of sintering furnaces. From a survey of the literature, we found that furnaces account for typically 40–60% of the equipment investment requirements [27,46]. On the basis of this finding, we assume in our model that the total level of equipment costs varies linearly with the expenses related to the acquisition of furnaces, for which we suppose a constant average contribution of 50% (see Eq. (10)). The remaining 50% is mostly spent on activities associated with the purchase of a range of other types of machinery, among which print-screening, drying and cutting equipment. To some extent this latter share may be spent on the realization of automation processes, but this cost component can be kept to a bare minimum. The investments associated with furnace purchasing scale with the number of furnaces (N_{fn}) needed. Given the current and anticipated growth in the SOFC manufacturing sector, these investments typically involve furnaces twice the size than actually dictated by the initially planned annual fuel cell production level. This prevents that furnaces need to be retired before the end of their designed lifetime because a plant requires a capacity extension already several years after its inception. We account for this effect in our SOFC cost model. Eq. (10) expresses that N_{fn} multiplied with the unitary furnace costs (c_{fn} in US\$(2008)), and corrected for the 50% share factor, yields the total equipment cost requirement [47,48]:

$$C_{eq} = \frac{N_{fn} c_{fn}}{0.5} \tag{10}$$

For the terrain plus building cost term (C_{tr}) we assume that an area of 30,000 m^2 is sufficient for the construction of an SOFC manufacturing plant for all production scales and potential expansions considered in this study. We estimate the corresponding investment requirements at 8.8 million US\$(2008). In practice, terrain plus building costs may be subject to significant geographic variability, but since we focus on Europe and the US in this article we may safely neglect such variations. In case a fuel cell production plant in e.g. China were to be considered, a separate analysis of terrain plus building costs would be required. Leasing the premises has not been considered in this study.

If the annual fuel cell production reaches the capacity limit of the plant, either new furnaces of the same capacity need to be purchased and installed in parallel to the existing ones, or the operational furnaces need to be replaced by bigger units. In case of the

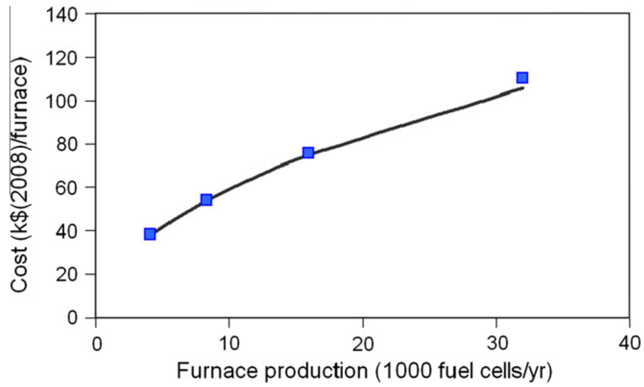

Fig. 3. Furnace purchase cost as function of its annual fuel cell production rate. Data from [47,48] and ECN [27].

latter, we simulate economies-of-scale effects, since the costs of furnaces are influenced by their annual production capacity. Fig. 3 depicts this relationship by a fit through data points gathered from various sources, which we adopt in our SOFC cost model. No cost data proved available for SOFC production rates higher than a level of 32,000 sintered fuel cells per year, typically the maximum that can be reached with conventional furnace types. We have attempted to investigate economies-of-scale effects for furnaces with larger production rates by inspecting innovative sintering techniques (including furnaces capable of processing 2000 fuel cells per single run), but found no reliable cost data [49].

A manufacturing facility is often subjected to up-scaling efforts in order to increase the number of fuel cells it can produce annually. The size or number of appliances and production lines then need to be expanded correspondingly. Of course, any up-scaling activity involves additional investments. For the plants included in our study, we ensure that the corresponding additional capital cost requirements are incorporated in our cost model through Eqs. (9) and (10). Similar to the inclusion of additional production capacity, we also account for effects of retirement and replacement of equipment such as furnaces. The costs incurred as a result of the amortization of new equipment investments are added to already existing annuities.

4. Learning curves for SOFCs

In order to construct a learning curve from the SOFC cost figures obtained with the model described in the previous section, we need data for the cumulatively produced or installed capacity of SOFCs.

4.1. Produced capacity

The annual capacity levels depicted in Fig. 4, both by manufacturer (left panel) and their total (right panel), show that SOFC technology is in the transition between the stage of pilot production and the phase of early commercial deployment. Furthermore, the right panel of Fig. 4 demonstrates that the SOFC production capacity of all main manufacturers combined, as well as the actual capacity of SOFCs annually produced, has been subject to exponential growth for more than a decade [50]. This implies that also cumulative manufactured capacity has grown exponentially. According to Ferioli and van der Zwaan, such production increases – if combined with exponential cost decreases – suggest the presence of learning phenomena for this technology [17].

We found reliable production capacity data for four major manufacturers. The US–Canadian company Versa Power Systems (Versa), presumably since several years the largest player in the field, increased its annual production volume of SOFCs rapidly from 1999 to 2001 in the context of the Solid State Energy Conversion Alliance (SECA) [51,52]. By lack of information on its annual production capacity from 2002 onwards, we assume that Versa maintained its capacity at its 2001 level of about 7 MW/yr since then. H.C. Starck from Germany (that bought InDec, a spin-off company established by ECN from the Netherlands) is currently the most important European manufacturer of SOFCs. For the past few years it possessed a production capacity of approximately 5 MW/yr, corresponding to some 300,000 fuel cells per annum [53,54]. Topsoe Fuel Cell (further referred as Topsoe) from Denmark started its commercial SOFC production activities more recently. In 2009, it reached a production capacity of about 5 MW/yr [55–58]. The strategy of CFCL from Australia is to contract out part of its SOFC production to German manufacturers. In 2009 it reached an overall production level of around 1.7 MW/yr [59].

These individual manufacturers typically report only total production capacity data for their facilities, and are reluctant to render publicly the number of actually produced SOFCs or, alternatively, the annual average production yield (load factor) or failure rate. Since we know levels of actually produced SOFCs only at the global level (see Fig. 4, right panel), and not per company, our model calculates learning rates on the basis of announced production capacity data. This leads to a systematic error as a result of the use of cost values that deviate from cost data corresponding to actually produced SOFC. We quantify the effect of this bias on the determination of learning rates through a sensitivity study.

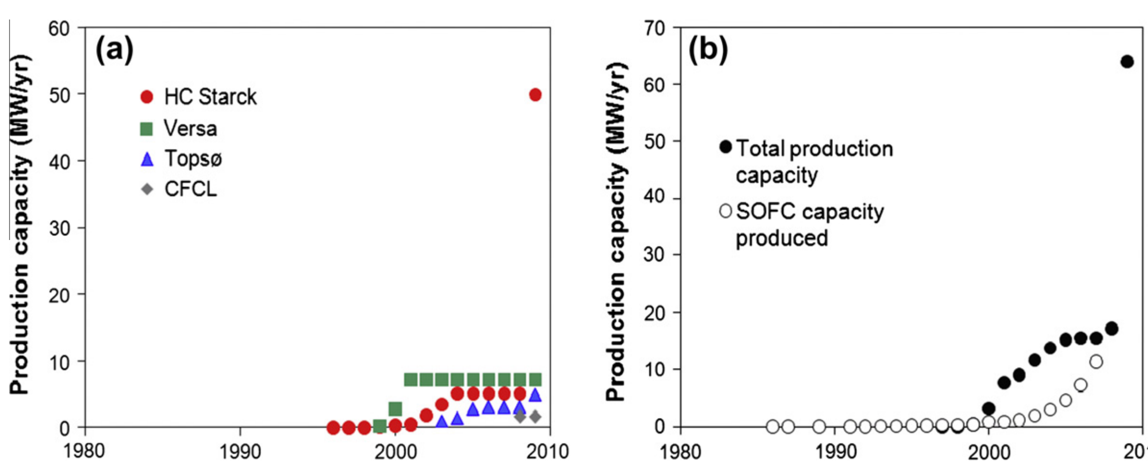

Fig. 4. SOFC production capacity of four main manufacturers (a) and total SOFC production capacity compared with the total capacity realized (b) [50–58].

An important facet of produced capacity figures is the production yield, that is, the relative number of SOFCs successfully produced per bulk of manufacturing. SOFC production failure can occur at many different stages, but most of the time it takes place during the sintering process or the steps of multilayer production and handling [25]. Recycling of scrap material and broken SOFC waste can in principle induce material and cost savings, but the introduction of these processes also incur expenses. We do not include these effects in our cost model. Fig. 5 shows failure rate data from the pilot production stage for three different SOFC manufacturers. We observe that during this phase the failure rate may go from levels as high as 70% down to a value of 10%. One also sees that these improvements can be expressed in the form of learning curves. The depicted failure rate decreases are likely to result from a combination of learning-by-doing and learning-by-searching effects in the pilot stage of the SOFC production process. These phenomena can lead to important cost reductions during a period that also significant material cost reductions are acquired as a result of learning processes. We find that at the early commercial stage the failure rate has typically dropped to 10–20% for each of the three considered manufacturers. After this, the scope for further economic improvements based on failure rate reduction is limited, while we suspect that those associated with material cost reduction, continue. Fig. 5 shows that pilot-phase SOFC production yield improvements can be expressed, quite consistently across different manufacturers from different regions, by a learning rate of 9–12%, which implies a corresponding experience-based decrease in the failure rate with every doubling of cumulatively produced SOFC capacity. We assume that strategy of how to improve the production yield is set by each manufacturer and can be either smooth and constant, like seems to be for Versa, or rapid when reaching the very early commercial production step, like seems to be for Topsoe. Independently of the latter, once early commercial production takes off, one frequently observes a minimum production yield rate of about 80%.

4.2. Manufacturing learning

With the cost values homogenized with our model plus the data available for the cumulative manufactured fuel cell capacity, we are now able to determine a learning curve for the production of SOFCs. We found cost and capacity data for the R&D, pilot and early commercial stages of SOFC development for the four major fuel cell manufacturers and study learning phenomena for the aggregation of these different phases as well as for each of them individually. In our analysis we only include data from facilities run by H.C.Starck, Versa and Topsoe, since CFCL has a significant share of its SOFCs manufactured in Europe. Apart from its capacity to render available cost data homogeneous – thereby enabling learning curve analysis – our model has as additional benefit that it allows for separately studying cost reductions driven by mechanisms other than pure learning phenomena. We start our investigation with the main European manufacturer H.C. Starck, since from this company (or InDec at ECN, to be more precise) we had access to a more detailed data set and other information regarding SOFC production during the earliest stage of manufacturing. Fig. 6 plots the resulting learning curve for the R&D phase of SOFC production, for which we estimate a learning rate of 16%. Given the low volume of fuel cells produced, the relative material and labor costs in this stage, and hence the total costs, are high. We depict these overall cost values in normalized terms for reasons of confidentiality. The accuracy of our cost model is confirmed by the observation that total cost figures derived from it deviate by at most 4% from similar data found in the literature.

We expand our learning curve analysis by extending the ECN-InDEC cost data from the R&D phase with those from the H.C. Starck pilot and early commercial production stages. The result is shown in Figs. 7 and 6, respectively. Fitting the data that correspond to the pilot phase yields a learning rate of 44%, while applying the same procedure to only those data that represent the early commercial production phase generates a learning rate of 5%. Making a linear regression of all data combined (R&D, pilot and early commercial production phases) implies $lr = 27\%$, a value a little higher than the average observed for scores of energy technologies. To arrive at these results, we assume in our model no cost reductions obtained through automation or economies-of-scale effects for furnaces: hence labor costs in Eq. (8) vary with $\beta = 1.0$ and equipment costs in Eq. (10) increase linearly with the number of furnaces purchased and remain thus unaffected by the effect displayed in Fig. 3. We do suppose, however, economies-of-scale effects for material requirements: the costs of NiO–YSZ drop with the volume purchased according to the strongly non-linear graph depicted in Fig. 2.

The learning rate we observe for the pilot stage of SOFC production is extraordinarily high. To a large extent, however, this elevated value proves to result from economies-of-scale for material costs. This effect, while an important driver for cost reductions, leads to a learning curve that cannot be considered to reflect pure learning phenomena. If, on the other hand, we assume in our model the costs of NiO–YSZ powder to be constant at 100$(2008)/kg, and thereby subtract the influence of material-based economies-of-scale from overall SOFC production cost reductions, we obtain

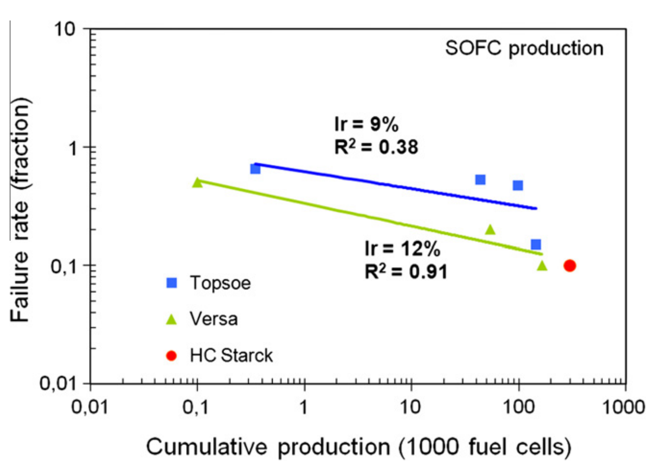

Fig. 5. Learning curves for the failure rate of SOFC manufacturing. Pilot stage production data from Versa, H.C. Starck and Topsoe [52–59].

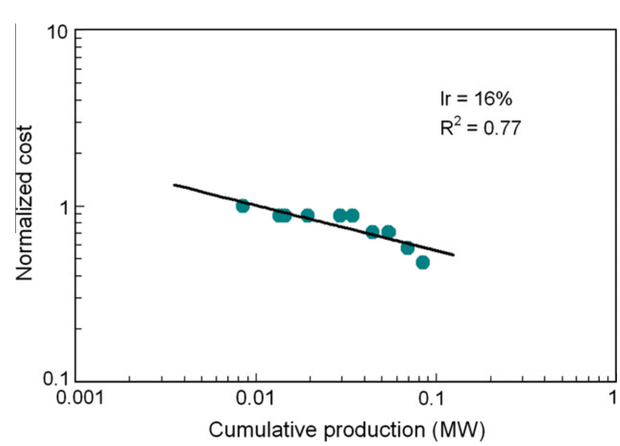

Fig. 6. Learning curve for the R&D stage of SOFC production. Data from InDec at ECN (later H.C. Starck) homogenized with our cost model [27].

a learning rate of 27%. This value, 17% lower than the value we found before, represents learning-by-doing proper. The early commercial stage is dominated by labor and capital costs, rather than material costs. The learning rate value of 5% estimated for this phase nevertheless proves to include a sizable effect from economies-of-scale of NiO–YSZ powder purchasing. When including solely genuine learning-by-doing phenomena our model generates a very low learning rate value, $lr = 1\%$.

We next turn our attention to potential supplementary cost reduction benefits driven by automation. Fig. 8 shows the pilot and early commercial production data from Fig. 7 transformed with values of the automation coefficient $\beta = 0.7$ (left graph) and $\beta = 0.2$ (right graph), and including economies-of-scale effects related to both material purchase volumes and furnace equipment investments. The learning rate reaches values of 35% and 39% for these low and high automation assumptions respectively. The equivalent data set – so including both pilot and early commercial production data, but excluding R&D phase data – with $\beta = 1.0$ generates a learning rate of approximately 33%. Hence the effect automation may have on SOFC production cost reductions, for these two stages combined, is clear, although not exceedingly large, however, the reduction on investments needed to cumulate SOFCs in order to reach their expected cost reduction appear to be significant.

For the R&D stage of H.C. Starck the available cost and capacity data correspond to accurate values of actual numbers of fuel cells produced. For further production stages, however, we need to use production capacities as proxy for the numbers of SOFCs fabricated. Given that our model is thus based on production capacity data, rather than the number of fuel cells manufactured, we implicitly assume a load factor of 100%. Since the load factor is likely to have been lower, we performed a sensitivity study with regards to the influence on our cost estimations from the value chosen for this load factor during the pilot and early commercial production stages. If we replace the 100% load factor by a value of 50%, for the H.C. Starck facility, we obtain $lr = 30\%$ instead of $lr = 35\%$ reported above for $\beta = 0.7$. We thus conclude that the maximum impact on the learning rate from an erroneous assumption regarding the load factor of a facility is 5%.

We studied cost data from Versa and Topsoe separately from those of H.C. Starck, since the facilities of these three companies are characterized by important variations in production capacity. Data from the former two involve capacity values typical for the end of the R&D stage of SOFC production. In Fig. 9 we present cost versus cumulative capacity data for these two companies homogenized with our cost model. Total estimated SOFC production costs prove to deviate by at most 13% from overall figures obtained directly from the public literature. For the R&D stage of SOFC manufacturing we find learning rates of 14% and 17% for Topsoe and Versa, respectively, as shown in Fig. 9.

We observe that the learning rates we calculated for the R&D phase of SOFC production by H.C. Starck, Versa and Topsoe are in

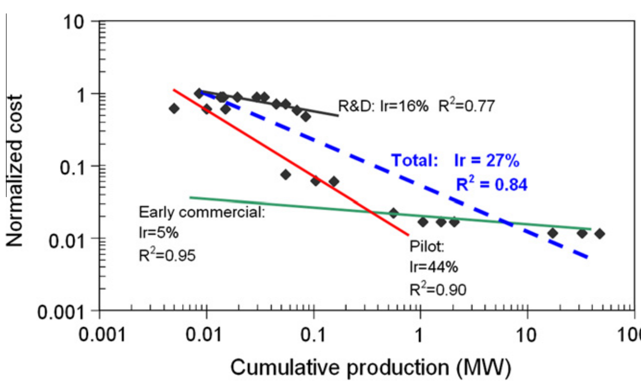

Fig. 7. Learning curves for the R&D, pilot and early commercial stages of SOFC manufacturing. Data from H.C. Starck homogenized with our cost model [27].

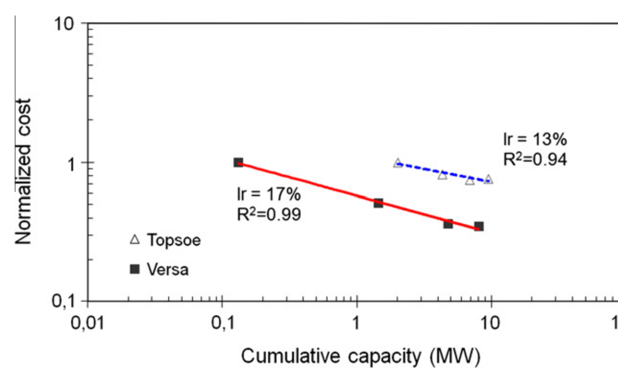

Fig. 9. Learning curves for the R&D phase of SOFC production in facilities operated by Versa and Topsoe.

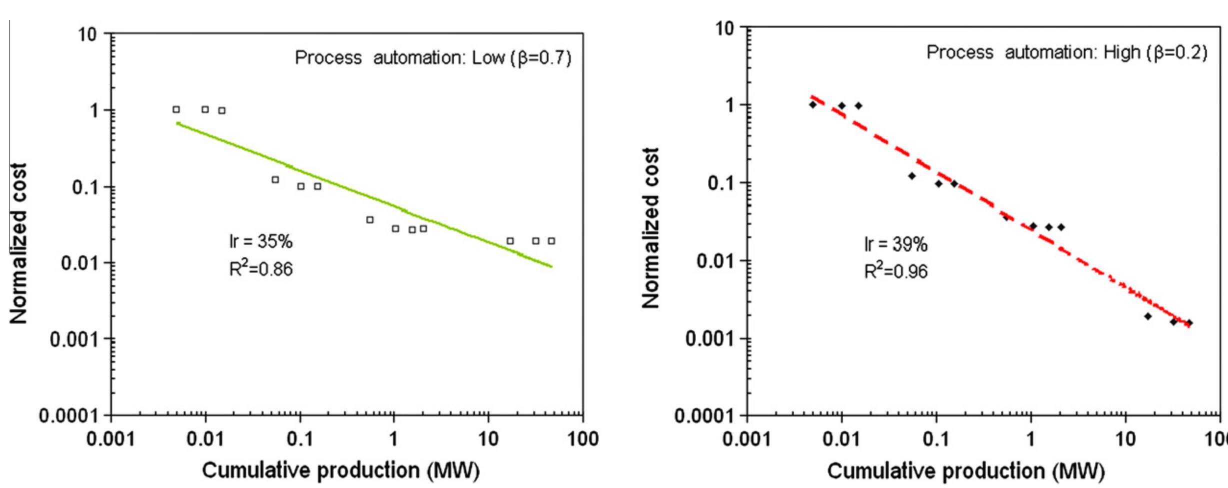

Fig. 8. Learning curves for the combined pilot and early commercial stages of SOFC production with multiple economies-of-scale but under different assumptions on automation effects. Data from HC Starck homogenized with our cost model [27].

good agreement with each other, irrespective of the discrepancies in production capacity for the plants they operate. Overall we may therefore safely conclude that within the R&D phase rather learning-by-searching than learning-by-doing phenomena can locally reduce SOFC production costs typically by around 13–17% with every doubling of cumulative produced capacity. Learning phenomena appear largest, however, at the pilot stage of manufacturing, and subsequently level off considerably during the early commercial production phase.

5. Discussion

The manufacturing cost model developed in the context of this study includes all important fuel cell production cost components. Since it also allows for estimating parts of overall cost data that in some open sources may not have been accounted for, it has the capacity to render SOFC manufacturing costs reported in different publications homogeneous. Our model's total SOFC manufacturing cost results prove to deviate by up to a maximum of 13% (but usually much less) from data found in the literature, which we consider largely acceptable for our purposes given the uncertainties the data we encounter in this domain are intrinsically characterized by. We thus consider the model fit for deriving learning curves and hence determining learning rates. Among its additional benefits are that it allows for calculating learning rates for different phases of SOFC production, as well as associated with different cost reduction phenomena. Table 1 gives an overview of the learning rates we were able to determine for the respective SOFC production phases of H.C. Starck (InDec), disaggregated by the four main cost reduction mechanisms we distinguish.

First, we observe that learning phenomena during the R&D stage can consistently be represented by an average regional learning rate of 16%, whatever the assumptions we make regarding economies-of-scale and automation. As we saw, this average learning rate originates from regional values we estimated for H.C. Stark, Versa and Topsoe facilities in their early R&D stage: 16%, 17% and 13% respectively (corresponding to 100,000 and 70,000 SOFCs produced annually). Given the consistency of our findings, we conclude that we here observe manufacturing process improvements that mainly take place because of learning-by-searching and include still a small contribution of learning-by-doing. The fairly high value of the learning rate constitutes an important indicator for future R&D activity with SOFC technologies. For instance, it may provide support for experimenting with new materials for the anode, cathode or electrolyte, or different techniques to produce or assemble them. To accurately picture the dynamics and precisely predict the impact of R&D investments, in terms of achieved cost reductions for SOFCs – as presented for wind energy in Ek and Söderholm [60] – is currently unfeasible because of a lack of public and private R&D investment data over the past years (partly as a result of confidentiality issues).

Second, Table 1 demonstrates that the main cost reduction potential lies in the pilot stage of larger SOFCs production. Moreover, the learning rate based on pure learning phenomena may be considerably lifted up if this mechanism is complemented with cost reduction effects related to economies-of-scale of materials usage (but not so much of equipment purchase) and the automation of labor, which are two mechanisms that differ from learning phenomena but are commonly expressed together. The total learning rate obtained for this phase, 44%, is at the very upper level of values that have been observed for (energy) technologies so far.

Third, rather surprising is that during the early commercial production phase we find little learning as a result of pure learning phenomena. The inclusion of cost reduction effects associated with economies-of-scale or automation, however, can increase the learning rate to a level of about 10%. Economies-of-scale resulting from the purchase of furnaces has the largest cost improvement potential: if combined with learning proper the learning rate amounts to about 12%. Even this value, however, is relatively modest in comparison to the learning rates observed for several energy technologies over the past decades, such as for PV cells and wind turbines. We assume that this low learning rate results from the high contribution of labor and capital charges to SOFC manufacturing costs. The latter means that important improvements on the technologies used to fabricate SOFCs are needed to enhance the learning rate.

During the phases of both pilot production and early commercial deployment, we conclude that manufacturing cost reductions take place as a result of a mix between all major drivers for cost reductions: genuine learning-by-doing, economies-of-scale for materials, economies-of-scale for equipment and automation. The distinction between the roles played by these four factors may be helpful for both strategic company planning and public policy making. In particular our ability to quantify each of them individually at different stages of production may be useful for allocating limited financial resources to this type of fuel cell development. Insightful in this respect is that our model can clarify possible interference effects between different sources of cost reductions. We see that the total learning rate (when one aggregates the data from all production phases) is at least 20%, independent on which underlying cost reduction mechanism is considered. The grand total of $lr = 35\%$, for all phases and mechanisms combined, is a high value: it in principle points towards the desirability of continued future efforts in the development of SOFCs.

Our model is obviously not perfect. Yet our extensive error analysis shows that our findings are robust. An improvement regarding the accuracy of the results could be reached by including a higher number of process details, such as concerning recycling strategies, R&D investments, waste management, chemical compounds disposal, maintenance costs and the availability of ceramic resources. Increasing the accuracy of the model, however, would accordingly render it more complex. We think that for our learning curve purposes the possible desirability of a higher degree of cost data precision would be outweighed by the lesser transparency that a more complex model would inevitably be characterized by. We have not studied cost reduction potentials for SOFCs other than planar ones, such as tubular designs, or entire SOFC systems – these are topics we hope to address in the future but fall beyond the more limited scope of this article.

Table 1
Learning rates for different phases of SOFC production by H.C. Starck, including or excluding effects of economies-of-scale and automation.

Learning rates (%)	Pure learning phenomena	Learning + Economies-of scale for only materials required for fuel cell manufacturing	Learning + Economies-of scale for only equipments required for fuel cell manufacturing	Learning + automation effects ($\beta = 0.7$)	All reduction cost phenomena
R&D stage	16	16	16	16	16
Pilot stage	27	44	28	36	44
Early commercial stage	1	5	12	10	12
All stages included	20	27	22	28	35

6. Conclusion

In this paper we present learning curves for SOFCs, which are increasingly used in CHP fuel cell systems. With data from fuel cell manufacturers we derive a detailed breakdown of production costs for SOFCs. We also develop a bottom-up model that allows for determining overall SOFC manufacturing costs from their respective cost components, among which material, energy, labor and capital charges. The results obtained from our model prove to deviate by at most 13% from total cost figures quoted in the literature. For the R&D stage, we find for SOFC manufacturing regional learning rates between 13% and 17%. When considering periods later in time, including the pilot or early commercial production stage, we find learning rates of 27% and 1%, respectively, if only genuine learning phenomena are considered. These figures turnout significantly higher, 44% and 12% respectively, if also effects of economies-of-scale and automation are included. When combining all production stages we obtain $lr = 35\%$, which represents a mix of phenomena such as learning-by-searching, learning-by-doing and mechanisms such as economies-of-scale and automation. This high learning rate value suggests that continued efforts in the development and deployment of SOFCs may lead to substantial further cost reductions in the future, potentially enabling their competitiveness with respect to existing alternatives. The learning rate values we found are high in comparison to those determined for a wide range of other (energy) technologies. It may prove unsustainable to maintain such high learning rates. We see some proof for their unsustainability by the leveling off of cost reductions at the accumulated capacity level realized to date. This would be consistent with the recent findings reported in [10], in which it is pointed out that the phenomenon of learning-by-doing tends to decay as a result of limitations in the cost reduction potential for certain components. In order to confirm whether learning may gradually fall, perhaps to values close to zero, as time and/or cumulative production proceeds, this topic needs to be subjected to further detailed research.

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