Learning Curves for Solid Oxide Fuel Cells

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Abstract

In this paper we present learning curves for solid oxide fuel cells (SOFCs) and combined heat and power (CHP) SOFC systems with an electric capacity between 1 and 250 kW. With data from fuel cell manufacturers we derive a detailed breakdown of production costs for both SOFCs and complete SOFC systems, that is, stacks of fuel cells plus their balance-of-plants (BoPs). We also develop a bottom-up model that allows for determining overall SOFC and BoP 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 early pilot stage of development, we find for SOFC manufacturing a learning rate between 14% and 17%, and for total SOFC system fabrication between 16% and 19%. We argue that the corresponding cost reductions result largely from learning-by-searching effects (R&D) rather than learning-by-doing. When considering a longer time frame that includes the early commercial production stage, we find learning rates between 14% and 39%, which represent a mix of phenomena such as learning-by-doing, learning-by-searching, economies-of-scale and automation.

Keywords: fuel cell, SOFC, cost reduction, learning-by-doing, economies-of-scale, automation

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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 efficiency relative to conventional gas and coal based power units: even in comparison to for instance an integrated gasification combined cycle (IGCC) plant their electric 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, methane or (a mix of) other hydrocarbon gases – takes place in the stack of fuel cells. The BoP supports the stack, drives the fuel through the fuel cells and can recover energy from the high-temperature exhaust gas.

In spite of their high electric efficiency and ensuing economic benefits, the fabrication costs of SOFC systems, and 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 only in the pilot stage and has not yet reached full 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 and the acquisition of experience through various learning processes at the stages of both manufacturing and usage. The rapidity of learning is usually expressed by the learning rate, a measure for the relative cost reduction of a good with every doubling of produced or installed capacity. The learning curve methodology allows for estimating the cost prospects of innovative technology and allows for determining the competitive breakeven point with respect to existing technology.

Schoots et al. [2] present an extensive analysis of learning phenomena for fuel cells, in particular for proton exchange membrane fuel cells (PEMFCs), phosphoric acid fuel cells (PAFCs) and alkaline fuel cells (AFCs). The present work aims to complement 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 (2004) 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 [3]. 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.

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
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. The developed learning curves may apply to a large range of different types of technologies and serve company strategic purposes and as a tool for public policy making. For the latter, we found information notably of 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, and is usually represented by a power law (See Equation 1). When cost and cumulative capacity data are plotted on a double-logarithmic scale, the power law of a learning curve becomes a downward sloping straight line. The slope of this line is called the learning index ($\alpha$) [9,10], which can be reformulated as the learning rate ($lr$) (see Equation 2). The latter expresses, usually in percentages, the relative cost reduction after each doubling of cumulatively produced items of a technology. In our fuel cells case, the variables in Equation 1 are the costs of SOFCs at time $t$ ($c_t$), the costs of SOFCs in the first batch of production (the time of which is referred to as $t = 0$) ($c_0$), the cumulated production of SOFCs at time $t$ ($P_t$) and the number of SOFCs in the first fabrication batch (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).

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

(1)

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

(2)

The learning rate summarizes how cost reductions materialize when a manufacturer accumulates production or, alternatively, when it contributes to cumulative production of a given technology thereby adding to the (global, regional or local) experience stock. 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 [11-15]. In the case of SOFCs, as well as many other technologies, a learning curve typically captures various kinds of contributions to overall cost reductions. It is conventional wisdom, and common practice in most studies, that learning rates are determined for technologies that have matured sufficiently and have completely 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 [16], 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 early-stage commercial production of SOFCs over recent years, motivated our attempt to develop a learning curve for this technology. Learning curve analysis can provide valuable insight for strategic planning and policy making, and can help determining or shaping indicators like total investment requirements and needs for subsidies or deployment levels for new energy technologies such as SOFC systems.

3. Cost requirements for SOFCs

Since SOFC systems operate at temperatures above 1000 K, they are principally considered for stationary and micro-stationary CHP generation purposes. Some mobile niche market applications exist, including in the transportation sector such as in trucks. Apart from their high electric efficiency, among their other particular benefits are that they may be designed in a variety of distinct forms and set-ups, and can run on different types of fuel [17-19]. In the current pre-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 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 fabricated usually of high performance stainless steel alloys [20-23]. 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, YSZ and LSM still constitute the state-of-the-art materials and are employed for the production of the vast majority of SOFCs. They are therefore the focus of the present study. Below 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 fuel cell width. The thickest layer usually defines which of the three acts as support of the fuel cell: anode, electrolyte or cathode. The other two function, and are deposited, as coating. For anode supported SOFC fabrication, currently the most widely adopted, the production process starts with tape-casting a slurry of NiO-YSZ, followed by drying the resulting sheets in order to get a solid and robust material. The electrolyte layer is added by spraying, tape-casting or screen-printing YSZ atop, followed by a sintering step well above 1400 K. The cathode layer is added by screen-printing LSM onto the electrolyte, after which the total assembly is
sintered again, this time at a lower temperature [24-26]. After the cutting process elementary fuel cells are formed by adding shaped interconnects to the multilayered ceramic units. A series of individual fuel cells are piled together to become an SOFC stack. For other kinds of fuel cell support – that is, cathode or electrolyte based – similar techniques are used but in a different sequence. For our planar SOFC study we assess the most commonly used method for multilayer ceramics manufacturing, which is the tape-casting of anode and screen-printing of 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 costs. 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 calculate accurately 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 [27]. The fuel cells studied in [27] use gasoline or diesel as fuel, reach a power density between 0.3 and 0.6 W/cm² and have an active surface of 100 cm². Total stack costs are estimated at 4–6 $/(2001) per 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 activity. 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 [24]. 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 single fuel cell, or 88 $/(2003)/kW. Koslowske describes a model similar to that of Woodward, and estimates a cost of approximately 3 $/(2003) per single fuel cell, or 56 $/(2003)/kW, for a production volume of 5 million fuel cells per year [28]. The information presented in these three publications is certainly interesting, but the 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 claims for higher production scales still need to be confirmed.

As demonstrated by a comparison of these three examples, fuel cell production costs heavily depend on the production volume because important opportunities exist 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 the potential benefits of economies-of-scale. A publication by Thijssen et al. [29] 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 can be 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 at the R&D and pilot stage, also their relative contribution to fuel cell manufacturing costs falls. Consequently, the contributions from the other cost components increase during the early phase of development of fuel cell production, in relative but not in absolute terms (See Figure 1-zoom). At full commercial production, however, the relative contribution of capital charges strongly increases and the relative contribution from labor drops mainly due to the automation of the production process (See Figure 1).

Figure 1 graphically describe how, as the production scale of fuel cells increases, labor costs progressively take the lead until the 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 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.
Figure 1. Relative contributions from the four main components of SOFC fabrication costs as function of the production scale, from the early phase to fully commercial development. Data from our model and Thijssen et al.[29].

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. 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 Equation 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 Equation 4). The total annual capacity is obtained by multiplying $N_{fc}$ by the fuel cell power density ($W_{fc}$) and its active surface ($A_{fc}$), expressed in kW/m² and m² respectively.

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

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

(3)

(4)
The drawback of Equation 3 is that the SOFC surface and stack length (hence capacity) vary significantly between manufacturers, so that cost figures are often hard to compare. Equation 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 inflation and exchange rates in order to further increase comparability. Depending on the year considered in this time frame we account for differences in salaries [30] and energy cost in the country in which the fuel cell production plant operates. We apply the respective correction factors necessary to obtain costs expressed in $(2008). This procedure ensures that all modeling results and literature data for specific costs are mutually as consistent as possible. Occasionally we normalize cost data for reasons of industrial confidentiality.

**Material costs**

Total annual material costs \(C_{\text{mat}}\) are estimated accounting volume and price of materials purchased per year by a manufacturing facility. This cost results by summing the products of the annually purchased material volumes \(m_{\text{NiO-YSZ}}, m_{\text{YSZ}}, m_{\text{LSM}}, m_{\text{int}}\) and their respective costs per kg \(c_{\text{NiO-YSZ}}, c_{\text{YSZ}}, c_{\text{LSM}}, c_{\text{int}}\), with the subscript \(\text{int}\) referring to interconnects:

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

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 granulisation 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/yr its price may be as high as 100 or even 200 $(2008)/kg [31]. 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 [32]. For YSZ and LSM the material costs for high purchase volumes reach values of typically 13 $(2008)/kg and 26 $(2008)/kg, respectively [33,34].

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 2 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 [32]. Hence, for all required substances we suppose that their costs at high volume consumption levels are limited to values only slightly above the corresponding raw material costs, to which thus no further cost reductions apply [34]. The total amount purchased of each powder is estimated on the basis of the density and thickness of each sintered layer [35-38], as well as the surface and number of SOFCs produced annually.
Figure 2 shows the costs per kg of NiO-YSZ powder for different annual consumption volumes, as well as our fit of the data points with a logarithmic equation. The result of our logarithmic regression is:

\[
c_{\text{NiO-YSZ}} = -6.4565 \times \ln(m_{\text{NiO-YSZ}}) + 66.553
\]  

(6)

SOFC manufacturers usually buy preformed thick plates of special stainless steel alloys, as fuel cell interconnects, for which on the basis of market prices we assume a constant cost charge of 275 $(2008)/kg. For the latter we considered that the variability of stainless steel prices, due to the sizeable diversity of alloys on offer as well as high market volatility, outweigh for instance possible scaling effects.

![Figure 2. Cost of NiO-YSZ powder per kg as function of volume purchased. Data points from [31] and [32], fitted by us.](image)

**Energy costs**

Apart from the material cost component, the energy input contribution to total SOFC fabrication costs is also particularly important. We assume that annual energy expenses \(C_{en}\) results from the total fuel cell capacity produced by a facility per year, the energy requirements per unit of capacity and the energy costs:

\[
C_{en} = N_{fc} \times W_{fc} \times A_{fc} \times \left( c_{el,kW} \frac{E_{el}}{3.6} \right)
\]  

(7)

In equation 7, \(N_{fc} \times W_{fc} \times A_{fc}\) represents again the total SOFC capacity annually produced, and the factor between brackets the energy costs incurred per unit of fabricated capacity expressed in kW. Only electric energy \(E_{el}\) is consumed during the manufacturing process of fuel cells. We homogenize the electric energy term in this equation, usually expressed in MJ/kW, by converting it into kWh/kW with the factor \(\frac{E_{el}}{3.6}\).
3.6. The number that results from the latter is then multiplied by the kWh electricity price \(c_{el,kWh}\), expressed in $(2008)/kWh, to obtain the energy cost component per kW of fabricated SOFCs [39]. We use electricity cost values that are an average between domestic and industrial prices as applied to the country under consideration and the point in time at which the fuel cells are manufactured. Equation 7 ascertains that the energy component to total SOFC manufacturing costs is appropriately homogenized and averaged over a year’s worth of fuel cell production activity by any given plant.

**Labor costs**

Especially in the early phases of fuel cell fabrication, labor costs are certainly non-negligible in the overall production process. For the level of annual labor expenses \(C_{lab}\) we only consider direct costs, that is, labor as related to the operation of the SOFC production facility. Secondary labor (such as associated with the multiple services offered to the plant and its operators) is not accounted for, 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 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 manufacturing and stack assembling is performed by typically five individuals full-time employed when an annual volume of 25000 fuel cells is produced [26,40]. We assume that \(C_{lab}\) is proportional to the gross Average Employment Income \((AEI)\) in the country of SOFC manufacturing under consideration [30] and that, with no automation, the number of individuals employed in the plant increases linearly with the fuel cell production scale:

\[
C_{lab} = AEI \left( N_{fc} \frac{5}{25000} \right)^\beta
\]  

Equation 8 is represented as a power law to account for the possibility of automation. In the case of non-automation, we put \(\beta=1.0\), 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 assume that Equation 8 becomes non-linear, with typically \(0.2 \leq \beta < 1.0\). 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.

**Capital costs**

Two main types of capital charges can be distinguished as investment requirements for the construction of a fuel cell production facility: equipment costs \(C_{eq}\) and terrain- and building costs \(C_{tr}\). Both represent figures for total capital costs per annum \(C_{cap}\) as
they are transformed from total investment values into annual capital costs through the annuities relationship for capital refunding:

\[
C_{\text{cap}} = (C_{eq}) \left( \frac{r}{(1 + r)^T - 1} \right) + (C_{eq}) \left( \frac{r}{(1 + r)^T - 1} \right)
\]  

(9)

in which \( r \) is the 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 Equation 9 and 10 is dominated by the purchase of sintering furnaces. From a survey of the literature, we found that furnaces account for typically 40% to 60% of the equipment investment requirements [26,40]. On the basis of this data, 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 Equation 10). The remainder share of 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), and to some extent on the realization of automation processes. If so desired, the latter cost components can be kept to a bare minimum. We calculate the investments associated with furnace purchasing on the basis of the number of furnaces \( (N_{fn}) \) needed to reach a 100% over-planned annual fuel cell production level. The latter allows furnaces to be kept working for longer periods and make use of them either until their lifetime limits or capacity. Equation 10 expresses that \( N_{fn} \) multiplied with the unitary furnace costs \( (c_{fn}, \text{ in US$}(2008)) \), and corrected for the 50% share factor, yields the total equipment cost requirement to be expressed per annum through Equation 9 [41,42]:

\[
C_{eq} = \frac{N_{fn} c_{fn}}{0.5}
\]

(10)

For the terrain 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). Nevertheless, being aware of the geographic variability of terrain costs, and on the cost of buildings construction to some extend, a separate analysis of fuel cells production cost including these capital charge elements will be performed.

Annual production capacity reaching the capacity limit of the furnaces will demand either the purchase of new furnaces of the same capacity to be installed in parallel or the replacement of the existing one by bigger units. For the latter, we include economies-of-scale effects in our model by assuming that the costs of furnaces are influenced by their foreseen annual production capacity. Figure 3 depicts this relationship by a fit through data points gathered from various sources. 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 expand economies-of-scale effects for furnace investment costs to larger production rates, by also inspecting innovative sintering techniques among which furnaces capable
of processing some 2000 fuel cells per single run, but found no corresponding cost data [43].

![Graph](image-url)

**Figure 3.** Furnace purchase cost as function of the annual production rate. Data from [41,42] and data from ECN.

A manufacturing facility is during its lifetime often subject to up-scaling efforts in order to increase the number of fuel cells produced annually. At such instances, the size or number of appliances and production lines needs to be expanded correspondingly. Of course, such up-scaling activity involves additional investments. For the plants included in our study, we ensure that corresponding up-scaling extra capital costs are incorporated in our cost model through Equations 9 and 10. Similarly, as with the inclusion of additional production capacity, we account for effects of retirement and replacement of equipment such as furnaces. Costs incurred by 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 SOFC cost figures, we need data of the cumulatively produced or installed capacity of SOFCs.

4.1. Produced capacity

The early commercial deployment of SOFC technology, and hence its ensuing production, shows to be leaving the stage of pilot production. In Figure 4 are presented both the exponential growing of fuel cell production and the installed production capacity of main manufacturers [44]. According to Ferioli and van der Zwaan, such production increase indicates that learning studies for this technology can be performed [16].
We found four major manufacturers: Versa, from USA and Canada, produced a rapidly increasing annual volume of SOFCs during the years 1999 and 2001 as part of the SECA project (Solid State Energy Conversion Alliance) [45]. Any further information about either the production capacity or extinction of the company is available. Hence, we assumed that this manufacturer maintained its annual production capacity since 2001 (7 MW/yr). Topsoe, from Denmark, is currently entering the early commercial stage of anode supported fuel cells, reaching a production of 5 MW/yr [46-49]. CFCL, from Australia, reached last year a production of 1.7 MW/yr. Their business model states that part of the fuel cell production would be carried out by German manufacturers [50]. Finally, HC Starck from Germany, and formerly InDec (ECN – Netherlands), is currently the most important European manufacturer with a production capacity of approximately 50 MW/yr (300 000 fuel cells per annum) [51].

It should be pointed out that mentioned manufacturers present production capacity data of their facilities instead of either the actual accurate number of fuel cells produced or the annual average load factor. Our model outcome is calculated on the basis of the announced production capacity, hence, cost values would deviate from cost available data that results from actual production capacity. As the latter might influence the learning rate, we will quantify this influence through a sensitivity study described later on.

An important facet of the produced capacity figure is the production yield of fuel cells, that is, what is the number of SOFCs successfully manufactured per production bulk. Failure on fuel cell production takes place mainly during the sintering step, followed by the multilayer production and handling steps [24]. Recycling of scrap material and waste disposal of broken fuel cells induces either to material savings or additional expenses not included in the cost model. We observe from available data that learning-by-doing and learning-by-searching phenomena allow for improving the fuel cell production process by significantly reducing failure rate down to only 10% (see Figure 5). The latter leads to important fuel cell cost reductions in R&D and pilot stage. However, as material costs are lowered to almost half when manufacture of fuel cells passes from R&D stage to early commercial stage, the economic impact of production...
failure rate is also strongly lowered. Improvement on the fuel cell production yield, or learning phenomena contributing to successful production processes, is presented in Figure 5. Our analysis show that effort on R&D and experience acquired results on 11% decrease on failure rate every doubling on cumulative capacity of fuel cells. Once early commercial production of SOFCs starts, a minimal yield rate of 80% is observed frequently.

![Learning curve for the failure rate of fuel cell production processes. Data from VERSA, Topsoe, HC Starck. [46-48,52,53]](image)

**Figure 5.** Learning curve for the failure rate of fuel cell production processes. Data from VERSA, Topsoe, HC Starck. [46-48,52,53]

### 4.2. Manufacturing learning

We present in this section the learning curve study for production cost of SOFCs. Available cost data derives from R&D, pilot and early commercial stages for the major fuel cell manufacturers. With exemption of CFCL, because of its business plan statements, this study deals with learning phenomena for both at each stage and total lifetime of HC Starck, Versa and Topsoe facilities. As means of a tool, our cost model enables to separately study cost reductions driven by non-learning phenomena, as well as rendering cost data homogeneous, and estimating additional cost values.

Commencing this section with the major European manufacturer (HC Starck), we plotted the learning curve for R&D stage based on our data (ECN - InDec) and on cost values derived with our model. We estimate the learning rate value for R&D stage at 16% (see Figure 6). Material and labor costs remain high and are not affected for the volume of fuel cells produced. Our estimated cost values confirm the accuracy of our model, deviating at most 4% from literature data.
We continue the learning curve analysis by gathering production cost values from R&D, pilot and early commercial production stages in the same plot (See Figure 7). As for R&D stage, we include cost data and modeled cost values. Cost reduction obtained through automation and economies-of-scale are not studied in this step of the analysis. We assumed that labor costs vary with $\beta = 1.0$ and $C_{eq}$ linearly increases.

During the pilot stage, we observe that the learning rate every doubling of cumulative capacity is up to 42%. However, economies-of-scale of material costs, not to be considered as learning phenomena, are an important driver for this reduction. In order to
clarify the latter, we estimated fuel cell production costs with our model subtracting the influence of economies-of-scale from material costs. Whether the purchase volume of powders, we assumed constant values for material costs. Learning rate results on a value of 27% and we suppose represents mainly pure learning-by-doing. Early commercial stage faces constrains against labor and capital costs, rather than material costs. The learning rate value is estimated at 5% and we suppose that learning-by-doing phenomena are mainly represented. Accounting the relevant impact of labor and capital costs since the early commercial production stage is reached we studied further potential cost reductions driven by automation. We carried out the comparison between learning curves built from fuel cell costs including coefficients of $\beta = 0.7$ and 0.2 (see Figure 8). Economies-of-scale related to material purchase volume and equipment investments are simultaneously considered. The learning rate reaches values from 35% to 39% for slightly to highly automation respectively.

![Figure 8. Modeled cost values for SOFC production under assumptions for automation and economies-of-scale effects. Data from our modeled and from HC Starck [26].](image)

As our model is based on production capacity data and accounting that HC Starck has the highest capacity among the major fuel cell producers, we performed the sensitivity study of the impact of pilot and early commercial production capacity on cost estimations. Cost data available and estimated, only for the R&D stage, were straightly retained as they correspond to accurate values of produced fuel cells. For further production stages, we supposed a 50% load factor of the HC Starck facility. The lr results on 30% for medium automated facility ($\beta=0.7$) instead of 35% estimated with 100% load factor. This enables to estimate a maximal impact on lr values of 5% derived from uncertainties in manufacturers load factor.
Accounting facility capacity important differences, cost data from VERSA and Topsoe facilities are studied separately. Both facilities present a capacity equivalent to a pilot stage. Homogenized data and modeled cost values are presented together in Figure 9. Estimated fuel cell production costs deviate at most 13% of literature data. Learning rates values are found between 14% and 17% (see Figure 9).

![Figure 9. Learning curves for SOFC production in VERSA and Topsoe facilities](image)

Learning rate values from HC Starck, Versa and Topsoe confirm that mainly learning-by-searching phenomena enable to reduce production costs by around 15%. Based on the fact that a confirmed value for learning curves is found at R&D and pilot production capacities, we will retain the costs and capacity data in order to go further with our learning curve analysis for SOFC systems.

5. Learning curves for SOFC systems

Does the learning we determined for SOFC manufacturing into learning for total SOFC systems? If so, is the learning for the latter different from the former? In order to answer this question we need to investigate the costs involved with the BoP manufacturing.

5.1. BoP costs

The components of a BoP are more mature from a technical point of view than SOFCs. For example heat exchangers, blowers, pumps and compressors are produced industrially and manufacturing techniques are well known. Nevertheless, adapting them to successfully fit the SOFC and fulfill their functions together with the fuel cell stack is still in progress. Like with the manufacturing of SOFCs, the fabrication of the BoP involves in principle four main cost components, related respectively to materials, energy, labor and capital. To analyze cost developments for the total SOFC system, we
extended our model to include these additional BoP related contributions to overall system costs [27]. Manufacturers of fuel cells produce and commercialize stacks that in most cases are integrated in the SOFC system by a third company. For purposes of this work, however, we assume that SOFC producers also build the entire systems.

**Material costs**

Total annual material cost estimations for the BoP ($C_{BoP,\text{mat}}$) are carried out on the basis of the prices and amounts of each material needed in the BoP production (see Equation 11). For the former calculation, we include the market prices for steel, stainless steel (S-Steel), zinc, nickel and aluminium. For the latter, we account for Karakoussis et al. [38] data for materials needed on BoPs for small power units (under 5 kW power output), expressed in kg/kW [54,55]. Costs of other materials such as plastics, copper and purified silica are not considered because their negligible contribution to the BoP fabrication costs.

$$C_{BoP,\text{mat}} = c_{\text{Steel}} \times m_{\text{Steel}} + c_{\text{S-Steel}} \times m_{\text{S-Steel}} + c_{\text{Zn}} \times m_{\text{Zn}} + c_{\text{Ni}} \times m_{\text{Ni}} + c_{\text{Al}} \times m_{\text{Al}}$$

(11)

The variables of this equation are defined as before and the indices refer to the respective materials and elements.

**Energy costs**

The annual energy expenses for BoP manufacturing ($C_{BoP,\text{en}}$) on the basis of the annual production capacity of systems that results from the product of the number of fuel cells per system, their power density and surface, and the energy per unit of system capacity. As in the energy costs for fuel cell production, the electric energy costs and the energy needed [38] during the BoP manufacturing process are defined as $c_{\text{kWh,e}}$ and $E_{BoP,el}$, respectively (see Equation 12). We thus get the following expression:

$$C_{BoP,\text{en}} = N_{f_{c,\text{system}}} \times W_{f_{c}} \times A_{f_{c}} \left( c_{\text{kWh}} \frac{E_{BoP,el}}{3.6} \right)$$

(12)

**Labor costs**

Information related to individuals needed to produce and assemble the BoP is highly scarce and heterogeneous. Thus, the number of individuals is assumed to be equal to the one for SOFCs manufacture. The total SOFC system labor cost would then become twice the value of fuel cell labor cost.

**Capital costs**

We assume that the capital costs related to the facilities in which the BoP is constructed (as well as the terrain on which the buildings are constructed) can be neglected. Indeed, the means required for these cost components are relatively small in comparison to the other contributions to overall costs.
5.2. System learning

Estimated cost values for 5 kW SOFC systems show that BoP contribution to total system manufacturing cost represents 64%. The latter fits with data provided by the consulting firm Arthur D. Little Inc. [27]. For different SOFC system capacities, the number of fuel cells contained in the stacks varies linearly with the requested power output. However, BoP would present a non-linear variation resulting on variable cost contribution, such as presented by Schoots et al. for PEMFC systems [2]. As the value of 64% is the only data point available for BoP contribution to SOFC system cost, we assumed that it would become the reference point for scaling contribution values for different SOFC systems presenting various power output values. The former is modeled by means of equation 13 under assumptions for an analogical behavior between PEMFC and SOFC BoP contribution to the system cost (see Figure 10). This results on the fit of the BoP contribution profile to the value of 64% (0.64 in equation 13) with a coefficient \( \gamma = 0.11 \). For further estimations, SOFC system cost is estimated on the basis of manufacturing cost of fuel cells needed to attain a certain system power capacity \( C_{K, fc} \) and on the contribution of BoP cost to the total figure.

![Figure 10. BoP cost contribution to total investment requirements for PEMFC and SOFC systems.](image)

\[
C_{\text{system}} = \frac{C_{K, fc}}{1 - 0.64 \times \left( \frac{N_{fc} \times W_{fc} \times A_{fc}}{5} \right)^{-\gamma}} \tag{13}
\]

The plot of modeled system costs based on R&D and pilot production capacities and data available derive on learning rate values for 1 to 250 kW SOFC systems between 17% and 19% (Figure 11). The refunding of capital charges for both fuel cell and BoP
side are not included in the costs plotted, but they would importantly increase the system cost depending on economic parameters used to discount investments.

![Figure 11. Learning curve for planar SOFC systems for 1 and 250 kW (electric power output). Modeled data and obtained from [27].](image)

6. Discussion

The manufacturing cost model developed here is based on the most important fuel cell cost components (materials, energy and labor) and is used to estimate homogeneous manufacturing costs for planar SOFCs. Results deviate up to 13% from literature data, which we consider as acceptable specially by accounting the fact that the components considered cover most cost contributions on fuel cell production. We are aware that an improvement on the accuracy of the results can be reached by including a high number of process details, such as those concerning data related for recycling, waste management, disposal of chemical compounds, maintenance costs and availability of ceramic resources. However, a highly accurate and complex model would lead to unnecessary precision on cost data that is not relevant for a learning curve study.

Excluding capital charges, data and estimated cost values show that the fuel cell system cost is near or even lower than the targeted values by the Department of Energy US (400 $/kW). Results enable to conclude that capital charges and related economical assumptions might strongly impact the production costs as from the early commercial stage. The latter slows fuel cell total production costs to truly reach the fixed cost target. We conclude that R&D and policy support of new fuel cell manufacturing methods might contribute to fuel cell deployment and further fuel cell cost reductions.

Material availability and cost variation due to international offer-demand phenomena seem not to be or become an urgent issue with an impact on SOFC production.
Lanthanum, yttrium, nickel, manganese and zirconium supply could be assured for the next years because ores are at least 1000 times more important than platinum [56]. The latter refers to constrains ensued by platinum role on the deployment of PEMFCs.

The estimated learning rate values for VERSA and Topsoe facilities, which are in pilot stage (100 000 and 70 000 SOFCs produced per year respectively), are correspondingly 17% and 14%. These values are comparable to the learning rate of 16% estimated for R&D and pilot stage of HC Starck-InDec. At this stage, we suppose that basically most of manufacturing process improvements take place because of learning-by-searching phenomena.

Otherwise, when we study HC Starck fuel cell production during the phase of pilot production and early commercial deployment, manufacturing cost reductions take place mostly by learning-by-doing phenomena mixed with economies-of-scale and automation effects. In order to closely analyze learning phenomena, and also to avoid the interference of other kind of phenomena, we calculated fuel cell manufacturing costs by respectively assuming non-scalable cost for equipments needed in the facility, constant value for material costs and proportional variation on individuals hired ($\beta=1.0$). Total learning rate is estimated at 27% and we assume mainly represents both learning-by-searching and learning-by-doing. In order to determine the durability of the learning rate, we forecasted the HC Starck fuel cell production for the next 8 years. The latter assumes a cumulative fuel cell production capacity of 1 TW. Results show that a ground floor learning rate is reached value equal to zero and suggest that the minimum production costs would be reached.

Concerning planar SOFC systems, for instance we assumed that any learning is taking place on the manufacturing process of the elements composing the BoP mainly because of the maturity of their production processes. Further studies might need to be performed in order to determine if these elements strongly influence the learning rate of this technology. However, as capital charges have proved to head among the main cost contributions in early commercial phase, we suppose that learning phenomena on the BoP side might barely impact reduction cost trends.

Tubular fuel cell systems, with different SOFC geometry but identical fuel cell materials, increase on popularity and market share [57]. Siemens is the main manufacturer and leader of this technology since the early 1990’s and has recently reached the early commercial phase [58-59]. The adapted bottom-up model, like the one here developed for planar SOFC systems, is used to estimate the production costs of tubular fuel cells and BoP. However, no overall cost data are available to compare them with our results. Moreover, the production installed capacity is unfortunately unknown (confidential) and although spread values found in several documents are often contradictory [60,61]. For instance, the development of an accurate learning curve for tubular units is unachievable.

7. Conclusion

The learning curves for SOFCs and their systems presented in this article are derived from modeled manufacturing costs as well as manufacturer data from the open
literature. We obtained values for SOFC learning rates by combining all their main cost components, that is, related to respectively materials, energy, labor and capital charges. The latter – expenses associated with investments needed to build manufacturing facilities – are considered separately in order to obtain results comparable to figures found in the literature. For the R&D and pilot stage of planar SOFCs, we obtained learning rates ranging from 14% to 17%. For the stages beyond, i.e. the early commercial phase, we modeled manufacturing cost data and applied corrections in order to eliminate effects from economies-of-scale and automation. These data in combination with production capacity figures from HC Starck formed the basis of our learning-by-doing analysis. We found a learning curve characterized by a learning rate of 27 ± 15%. If phenomena of automation and economies-of-scale, as additional major drivers of cost reductions, had been taken into account, we would have obtained a learning rate of 39%. We point out that such a high rate is unsustainable. At any rate, in this and other papers we demonstrate that the phenomenon of learning tends to decay, and gradually phase out towards zero, as time and cumulative production proceeds. Optimistically, i.e. when the currently observed learning pertains, we estimate that manufacturing costs approach the ground floor of raw material costs when at least 1 TW worth of SOFC capacity will have been installed. Based on real and modeled cost data from facilities run by VERSA and Topsoe, we find learning rates between 17% and 19% for SOFC systems with an electric output between 1 kW and 250 kW. These values correspond well with observed learning rates determined for a wide range of other energy technologies. We have not been able to observe learning effects for the BoP part of total SOFC manufacturing costs. Like with planar SOFCs, we developed a cost model for tubular SOFC systems. A lack of cost and installed capacity data, however, did not enable us to derive an accurate learning rate for such designs, even while our preliminary estimates indicated a value of around 27%. Further work is needed to confirm this figure.

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