Received: 10 January 2019 | Revised: 13 February 2019 | Accepted: 20 February 2019
DOI: 10.1002/amp2.10011

RESEARCH ARTICLE

JOURNAL OF ADVANCED MANUFACTURING AND PROCESSING WILEY

The economics of numbering up a chemical process enterprise

Robert S. Weber | Lesley J. Snowden-Swan

Pacific Northwest National Laboratory, Richland, Washington

Correspondence
Robert S. Weber, Pacific Northwest National Laboratory, PO Box 999 MS-IN K2-12, Richland, WA 99362.
Email: robert.weber@pnnl.gov

Funding information
U.S. Department of Energy, Grant/Award Number: DE-AC05-76RL01830

Chemical-processing plants that can be numbered up by installing and operating many replicate facilities are economically and technically well suited for the conversion of geographically distributed sources of renewable or waste carbon into fuels or chemicals. Examples from the manufacture of chemicals and the installation of flue gas treatment technology suggest that the relative cost diminution should correlate through a power law ($\mathrm{Cost}/\mathrm{Cost}_1 \propto E^{-a}$) with E, a measure of the experience of operating those facilities and/or the number of units that are mass manufactured and installed. The exponent, a, can be related to the complexity of the process and the characteristics of the products.

KEYWORDS
learning, modular manufacturing, technoeconomic analysis

1 | INTRODUCTION

This overview borrows liberally from other industries and previous analyses of the manufacturing of fuels and chemicals[1] and pollution abatement[2] to present correlations that may be useful in estimating the economics of *numbering up* a distributed chemical process. The target example will be the production of chemicals and intermediates derived from feedstocks that are now disposed as waste (eg, sewage sludge, manure) and that therefore may be cost-advantaged over less noisome feedstocks generated purposely for making the products, for example, a purpose-grown energy crop.

If the inputs (viz., feedstocks, energy) to a chemical process are derived from geographically dispersed sources that are expensive to aggregate or if delivery of a product would benefit from very close proximity to its customers, then an enterprise consisting of many replicate facilities that satisfy the distributed market should be preferred to a centralized facility that operates at the same rate of production. The preference could arise, as it may for process intensification, because of economics,[3,4] resiliency,[5] or safety.[6] Examples of distributed feedstocks (inputs) include flue gas; renewably sourced electricity (in the absence of a lossless grid); and biomass and wastes from farms, landfills, or water treatment plants. Examples of dispersion-benefited products include shelf life-limited pharmaceuticals, highly reactive reagents (eg, Cl_2, H_2O_2, performic acid), and other intermediates that enhance a just-in-time production strategy.

2 | DISCUSSION

Chemical engineers are well schooled in estimating the economics of *scaling up* a process through the use of Lang factors and allometric relations between production capacity and unit costs,[7,8] particularly for stick-built facilities (ie, those constructed on site). The benefits of modularization[9,10] discussed to date deal with the ease and rapidity of assembly or installation, not the sort of mass manufacturing that is susceptible to economies of manufacturing scale, which is the topic here.

The term *enterprise* refers to either a conventional centralized facility or the aggregation of the distributed facilities. Thus, a 100 ton/day enterprise could mean either a centralized facility that operates at that rate of production or a set of 100 individual 1−*t*/day facilities, distributed to be close to the feedstocks or customers.

The term *experience* refers to the cumulative operation of either enterprise. It includes both the learning associated with the construction of plants beyond the pioneer installation as well as the refinements gleaned from time on stream.

Centralized plants are typically stick-built to accommodate unique demands of the site and of the customer. They are rarely numerous, identical replicates, so there is no opportunity to benefit from economies of learning from mass manufacturing.[11] Experience in this instance therefore typically signifies time on stream or cumulative throughput.

Distributed plants, on the other hand, would most likely consist of prefabricated, modular components, so experience can include the learning associated with designing, fabricating, assembling, and installing the plants, as well as the learning gained through operating the fleet of replicate facilities.

3 | EXPERIENCE CURVES

The cost of a produced unit, whether it is a service, a material, or a widget, is generally found to decrease with experience[12,13](Figure 1). Again, experience can include cumulative production and/or cumulative hours spent on stream. This type of correlation was initially attributed to learning by workers on assembly lines[14] but has been observed in other industries as well,[13] so it may also include learning by management, improvements in the manner of production, decreases in the cost of inputs, and other factors.[2] The exponent, a in Figure 1, is related to a quantity called the *progress ratio*, $p = 2^{-a}$; each doubling of experience lowers the per-unit cost by a factor, $(1-p)$, called the *learning rate*. Therefore, the smaller the progress ratio, the larger the learning rate and the faster the cost reduction; a progress ratio of 100% means that costs do not decrease with experience.

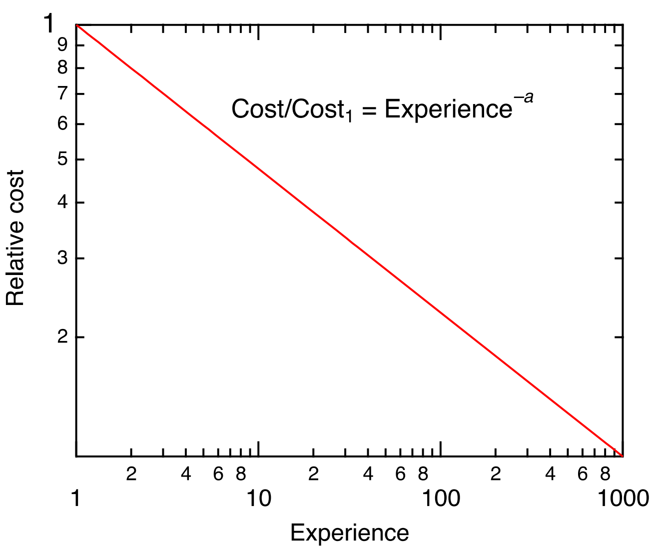

FIGURE 1 Prototypic experience curve showing how cost, relative to the initial cost, varies with an assumed learning rate = 20%, that is, a progress ratio, $P = 80\%$, $-a = 0.32 = -\log_2(0.8)$

For stick-built plants,[11,15] learning ratios for construction appear to be no larger than about 10%. However, several examples from the chemical process industry can exhibit cost savings that scale with experience equated with cumulative throughput[1,2] as exemplified by Figure 1.

A survey by Merrow[1] of more than 40 chemical processes, which included operating experiences as well as construction experience, has demonstrated progress ratios closer to 80% (ie, learning rates averaging about 20%), the trend varying with the complexity and other characteristics of the process and product:

Progress ratio,

$$\begin{aligned} p = 92.3 - 3.2\% &* \text{number of chemical processes} \\ &+ 6.5\% \text{if the main process train involves solids handling} \\ &+ 5.0\% \text{if the product is a primary chemical} \\ &\quad (\text{eg, sulfuric acid}) \\ &+ 5.0\% \text{if the product is a liquid} \end{aligned} \tag{1}$$

Of course, there are exceptions to the highly empirical observation of the effects of experience, with respect to the rate of learning rate, its constancy, and even its general progress; there are well-documented examples of forgetting as well as learning.[15–18]

An example that does show cost savings from experiential learning, flue gas desulfurization (FGD), is presented in the next section. Implications of cumulative learning for distributed processing of waste carbon resources will be discussed subsequently.

3.1 | Flue gas desulfurization

FGD consists of three principal operations (Figure 2) that serve to remove sulfur dioxide, produced from burning fuel-borne sulfur, most usually as calcium sulfate, which can either be sold as gypsum or disposed.

The history of the technology and its implementation of FGD, from 1971 through 2004, have been reviewed.[2] The capital costs for this necessarily distributed chemical process exhibited a progress rate of about 88% (ie, a learning rate of 12%) across a 30-fold increase in experience, represented by the capacity installed during that period (Figure 3). As mentioned above, that learning rate is typical of stick-built facilities, perhaps due to the customization required to retrofit each unique site.

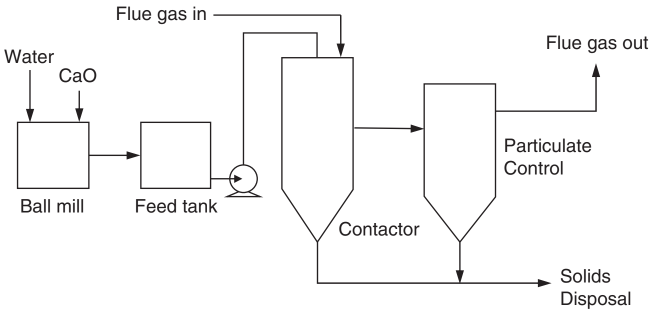

FIGURE 2 Schematic of the unit operations comprising flue gas desulfurization. The history of the technology and its implementation of FGD, from 1971 through 2004, have been reviewed.[2] The capital costs for this necessarily distributed chemical process exhibited a progress rate of about 88% (ie, a learning rate of 12%) across a 30-fold increase in experience, represented by the capacity installed during that period (Figure 3). As mentioned above, that learning rate is typical of stick-built facilities, perhaps due to the customization required to retrofit each unique site

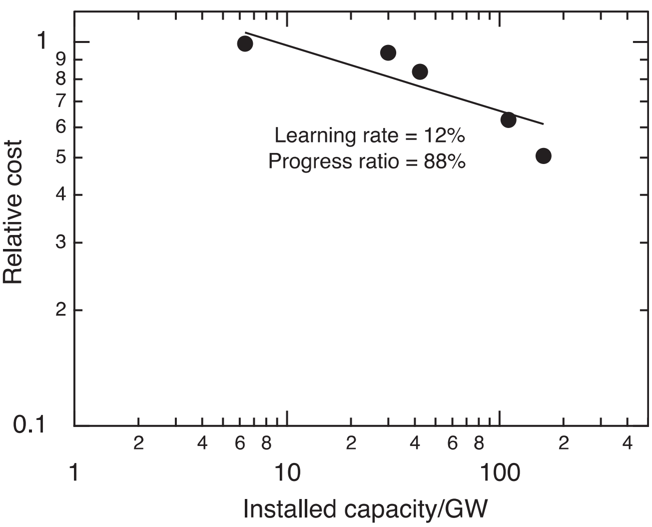

FIGURE 3 The capital cost of flue gas desulfurization (from data presented by Rubin et al[2]) decreases with experience, represented by cumulative installed capacity

According to that formula and the schematic process flow diagram shown in Figure 2, the progress ratio for FGD would have been predicted to be:

$$p_{\text{fgd}} = 92.3 - 3.2\%^{*}4 \text{ process steps}$$
$$+ 6.5\%(\text{for handling the calcium oxide and gypsum})$$
$$= 86\%(\text{cf } 88\% \text{from Figure 3}).$$

The agreement between the observed effects of experience on the capital expense of FGD and that predicted according to the correlation devised by Merrow[1] is notable. However, the data illustrate, as has been found elsewhere,[16,19–21] that the rate of learning may be only approximately constant across the phases of development and implementation of a technology (Table 1).

3.2 | Distributed processing of waste carbon

We have recently overviewed[3,4] the conversion of waste carbon into fuels and chemicals. A large number of plants would be needed to contend with the many, widely distributed sources of renewably produced biomass and carbon-containing waste streams. Therefore, such an enterprise would involve the fabrication, installation, and operation of facilities, whose economics would benefit from both manufacturing learning and operational learning. As an example, consider that the United States has about 15 000 municipal wastewater treatment plants[22] and about 40 000 dairy farms[23] that produce sludge and manure, which can be converted into a bio-oil via hydrothermal liquefaction.[24] We have estimated the cost of constructing a process that couples the hydrothermal liquefaction with electrochemical upgrading (HTL-ECU) of the bio-oil (Figure 4) at a scale in the range of 1 to 10 barrels/day of bio-oil (ca 1 *t*/day of liquid product). The cost estimates were derived from the Aspen Capital Cost Estimator,[25] scaled allometrically (exponent $\simeq$ 0.6) to this very small scale. We assumed a Lang installation factor of 1.7, corresponding to the installation of a new modular facility at an existing site (Scenario 4 of Sievers et al[10]). The capital costs for the depolymerization operations (HTL) and balance of plant were taken from a preliminary Pacific Northwest National Laboratory estimate.[24] The capital cost for the electrolysis reactor was adapted[3] from a detailed technoeconomic analysis of a redox flow battery.[26] At this early stage, we consider those

TABLE 1 Preliminary estimate of the capital expense (CapEx, Projected to 2016) for the fixed equipment for a first-of-a-kind and 1500th copy of a facility for depolymerizing waste biomass via hydrothermal liquefaction and electrochemical upgrading under two learning regimes

Unit	Installed CapEx for first 10-bbl/day plant	Installed CapEx for 1500th 10-bbl/day plant with $P = 90\%$	Installed CapEx for 1500th 10-bbl/day plant with $P = 80\%$
HTL production	\$920 000	\$303 000	\$87 400
Electrolyzer	\$98 000	\$32 200	\$9300
Installation	\$645 000	\$212 200	\$61 300
Cost per barrel per day	\$166 300	\$54 740	\$15 800

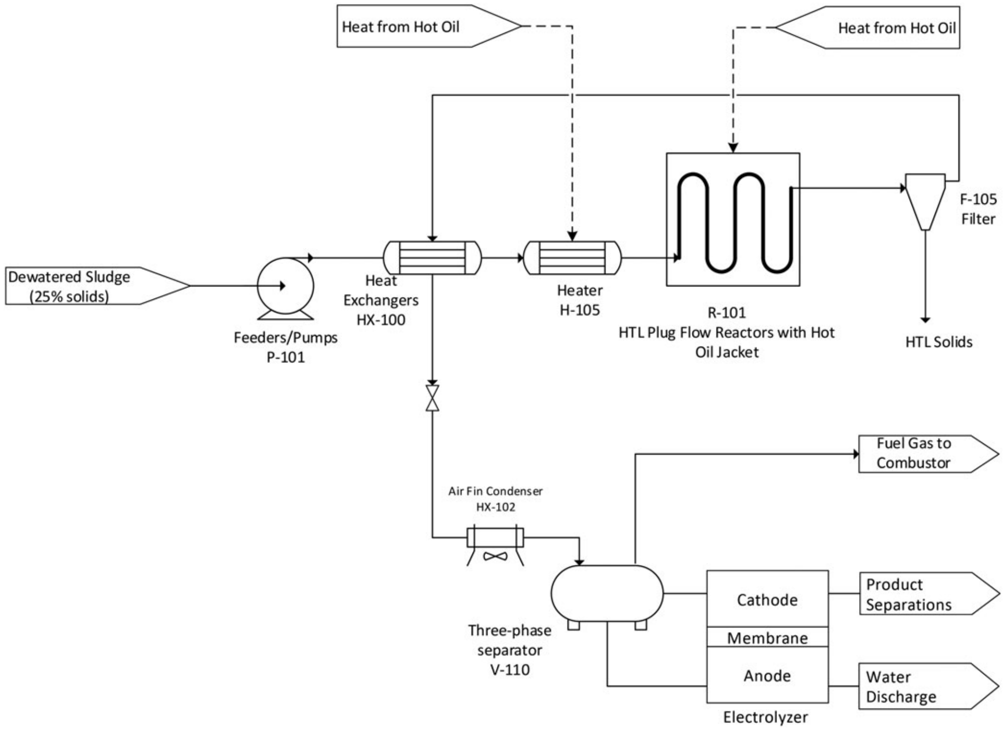

FIGURE 4 The schematic of a process that combines hydrothermal liquefaction of manures and sludge with electrochemical upgrading of the bio-oil and purification of the water

costs to be plausible but highly uncertain, in part due to the excessively large range over which we downscaled the equipment costs.

We have chosen to estimate the cost for the 1500th installation, which corresponds to an enterprise comprising the equivalent of 15 000 bbl/day of production, which is in the range considered for biorefineries.[27]

We considered two learning regimes (Table 1), one characteristic of stick-built plants (p = 90%) and the other corresponding to a value of p = 80% estimated from Equation 1, assuming eight unit operations (three of which reside in the electrolysis cell: oxidation at the anode, reduction at the cathode, and ion transport across the membrane):

$$\begin{aligned}&\text{Progress ratio}_{\text{HTL-ECU}}\\&= 92.3 - 3.2\%{*}8(\text{thermo} -)\text{ chemical steps}\\&+ 5\%(\text{for a primary chemical})\\&+ 5\%(\text{for a liquid product})\\&= 77\%(\text{which, to be conservative, we rounded up to }80\%).\end{aligned}$$

Those two values approximate the range of learning rates characteristic of facilities generating renewable electricity[20]: photovoltaics, where p = 73%, and wind turbines, where p = 89% (Figure 5).

If the product of the HTL-ECU process was a fuel feedstock that could be sold at a profit of, say, \$30/bbl, then the estimated capital expense for a 10-bbl/day facility that followed 20% learning would be paid back in about 1.5 years:

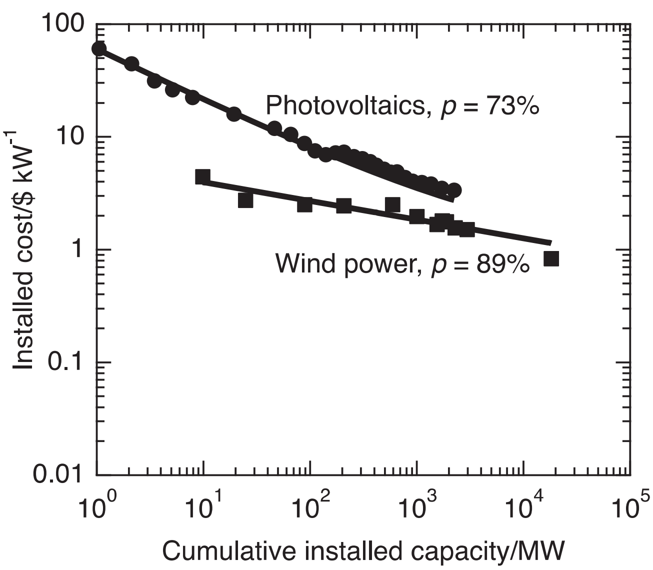

FIGURE 5 Comparison of the learning rates for the installation costs of two sources of renewable electricity from data reported by Nemet[20]

$$15,800/(30/\text{bbl}{*}1\text{ bbl/day}{*}365\text{ day/year}) = 1.4\text{ year}$$

and about 5 years if the learning rate was only 10%:

$$54,740/(30/\text{bbl}{*}1\text{ bbl/day}{*}365\text{ day/year}) = 5\text{ year}$$

Either should be well within the economic grasp of a municipality or even an individual investor. Of course, a well-considered investment would include detailed operating

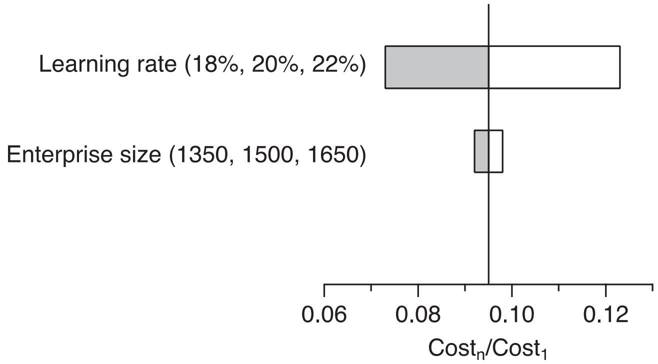

FIGURE 6 Sensitivity of the relative cost of the *n*th replicate (C_n/C_1) to the learning parameters near the base case (learning rate = 20%, enterprise size = 1500 units)

costs, as well as the likely negative cost of the feedstock (the tipping fee for sludge can exceed \$100/t).[28]

The effect of learning on the capital cost is, as would be expected, sensitive to the value of the learning rate; it is much less sensitive to the size of the enterprise (Figure 6).

4 | CONCLUSIONS

The economic effect of experience, which is frequently captured as a rate of learning, is an empirical correlation that needs to be adjusted and validated for each case. However, evidence from several examples of chemical processes suggests that their economics are susceptible to the benefits of experience, not just scale. The effects of learning will be critical to the economic success of chemical processing of distributed resources (and products) where aggregation may not be sufficient to justify the scaling typical of the approach that is conventional in enterprises for the chemical-processing industry.

ACKNOWLEDGEMENTS

This work was supported by Laboratory Directed Research and Development funding at Pacific Northwest National Laboratory (PNNL). PNNL is a multiprogram national laboratory operated for the US Department of Energy by Battelle under contract DE-AC05-76RL01830.

CONFLICT OF INTEREST

The authors declare no conflict of interest from the analysis or opinions expressed here.

ORCID

Robert S. Weber https://orcid.org/0000-0003-3731-8461

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How to cite this article: Weber RS, Snowden-Swan LJ. The economics of numbering up a chemical process enterprise. *J Adv Manuf Process*. 2019;1:e10011. https://doi.org/10.1002/amp2.10011