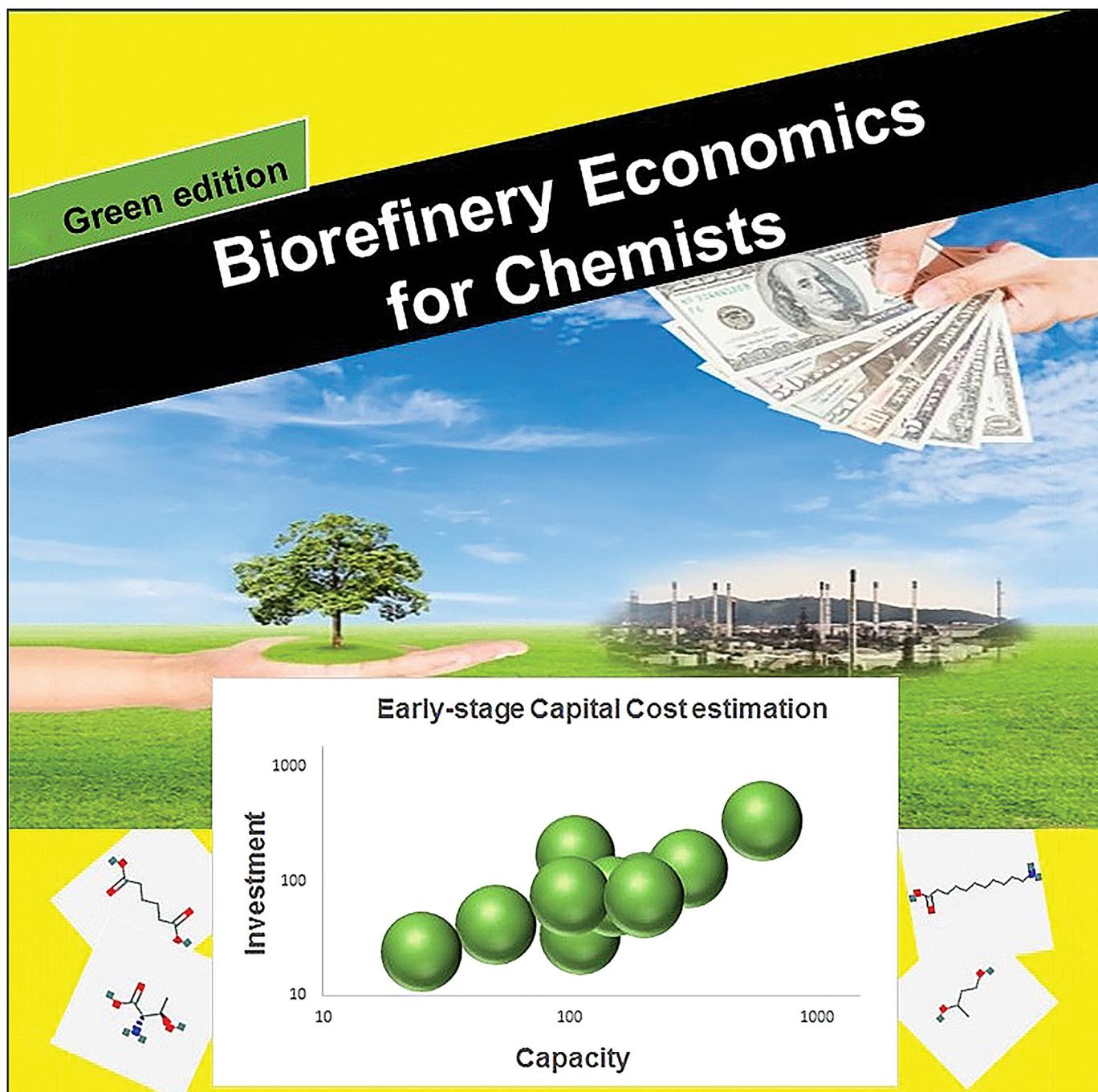


Early-Stage Capital Cost Estimation of Biorefinery Processes: A Comparative Study of Heuristic Techniques

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Biorefineries offer a promising alternative to fossil-based processing industries and have undergone rapid development in recent years. Limited financial resources and stringent company budgets necessitate quick capital estimation of pioneering biorefinery projects at the early stages of their conception to screen process alternatives, decide on project viability, and allocate resources to the most promising cases. Biorefineries are capital-intensive projects that involve state-of-the-art technologies for which there is no prior experience or sufficient historical data. This work reviews existing rapid cost estimation prac-

tices, which can be used by researchers with no previous cost estimating experience. It also comprises a comparative study of six cost methods on three well-documented biorefinery processes to evaluate their accuracy and precision. The results illustrate discrepancies among the methods because their extrapolation on biorefinery data often violates inherent assumptions. This study recommends the most appropriate rapid cost methods and urges the development of an improved early-stage capital cost estimation tool suitable for biorefinery processes.

1. Introduction

There is currently tremendous interest in promoting the production of renewable fuels and chemicals. The main drivers towards a biobased economy are the search for alternative carbon sources and the need for more sustainable production routes (i.e., economic, environmental, social),^[1] with the aim of reducing energy use and pollution emissions, while producing long-term job opportunities by stimulating rural and regional development.^[2] Biorefinery is a new concept, built on the analogy of traditional refineries, to describe plants utilizing a wide variety of biomass types that employ thermal, chemical, biological, physical, or a combination of conversion processes to produce fuels and a platform of chemicals.^[3] Biorefineries can be energy-driven or chemical-/product-driven. The energy-driven biorefinery aims to produce fuels, power, and/or heat while residues are upgraded as biobased products to optimize profitability. The chemical-/material-driven biorefinery aims to produce biobased products while residues are used to optimize the profitability of the value chain. The concept of an integrated biorefinery aims to combine different technologies and raw materials to optimize production and feedstock use.^[4]

A biorefinery is capital-intensive and this is why only a few operate today on a commercial scale.^[4] Biochemical processes include complex biological steps with low productivity and conversion yields, which require elaborate separation and purification systems, whereas large bulk raw materials and substantial amounts of solvent are translated into large equipment sizes. Thermochemical biorefineries operate under extreme process conditions (high pressure and temperature), which re-

quire special materials of construction, other than carbon steel, and special equipment is dedicated to the handling, treatment, and storage of bulk solid feedstock (i.e., lignocellulosic biomass, grains). The coproduction of heat or electricity for energy-intensive processes demands special energy production systems. These are just a few factors that can make biorefineries a costly and rather unattractive investment.^[5]

Limited capital budgets and competition for acquiring government funding and financing from investors put high pressure on engineers to design efficient biorefineries at low costs and on researchers to find the leanest chemical route. Capital estimation is, therefore, crucial at all design steps, from early stages and throughout the development of the project until the plant is finally commissioned and ready to go online. Capital cost estimation of biorefineries follows similar patterns to those of any new chemical processing plant.

1.1. Background

Capital cost or investment cost estimation is the first factor to determine project viability and it is made at all stages during project development, commonly known as the front-end loading process (FEL).^[6] Expansion, revamping, and retrofitting of existing plants or the construction of new ones is required by technological advancements and new product development.^[7] Researchers undertake the laborious task of predicting capital expenditure at the very early stages of process conception to assess alternative routes and viable process configurations based on limited information. If the project is approved, then the cost appraisal is an iterative process for monitoring actual expenses against initial estimates during project implementation.^[8]

There are two major categories of cost estimation: grassroots (or greenfield) and battery limits. Grassroots refers to the estimation of the entire plant comprising of field preparation, buildings, processing facilities, utilities, services, and storage. The processing facilities are also called inside battery limits (ISBL) and refer to the area where production takes place. Outside battery limits (OSBL) or offsites include the rest of the direct capital cost.^[9] Fixed capital investment is composed of direct and indirect costs. Direct capital cost (DCC) refers to the sum of ISBL and OSBL, whereas indirect capital cost refers to the engineering, construction, and contractor expenses. Working capital consists of funds necessary to pay operating ex-

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penses, raw materials purchase, accounts receivable/payable, and taxes payable, whereas start-up expenses cover the cost of employee training and equipment adjustment at the start of the project (Figure 1).^[9a,10]

Different sources propose slightly different nomenclature for the cost categories; thus, it is important that all cost elements are taken into account when estimating capital costs.

The classification of capital cost estimates is still not universally standardized, despite efforts that have been made to overcome this problem. The Association for the Advancement of Cost Engineering (AACE) identifies five major classes of cost estimation based on common practices among process industries around the world, whereas other associations adopt dif-

ferent schemes, which are presented in Table 1.^[6] For example, Class 5 is also called Order of Magnitude by ANSI and ACostE. A standardized approach would help to avoid any confusion or misunderstanding related to terminology and accuracy of estimation.^[11] Not all stages of estimation are to be followed, depending on market conditions, the maturity of the project, and if the company has previous experience in building a similar plant.^[8] As more details on the project are defined, the accuracy range of the estimate narrows. Furthermore, the European Commission identifies nine technology readiness levels (TRL) as a metric system to evaluate the research and development progress, define the maturity status of a technology, compare different technologies, and decide on further fund-

Mirela Tsagkari graduated from the School of Chemical Engineering at the National Technical University of Athens in 2012. Her diploma thesis (partially completed at the University of Surrey) focused on biorefinery economics with a special view on early-stage cost estimation methods. She continued working in the field for six months as part of the BIOCORE project on lignocellulosic-based biorefineries techno-economic evaluation. After working for six months at S&B Industrial minerals, she joined Arkema in April 2014 to continue her research in biorefinery cost engineering within the FP7 Marie Curie program "RENESENG". Her research focus has turned into developing a new cost estimation method suitable for biorefinery processes under development.



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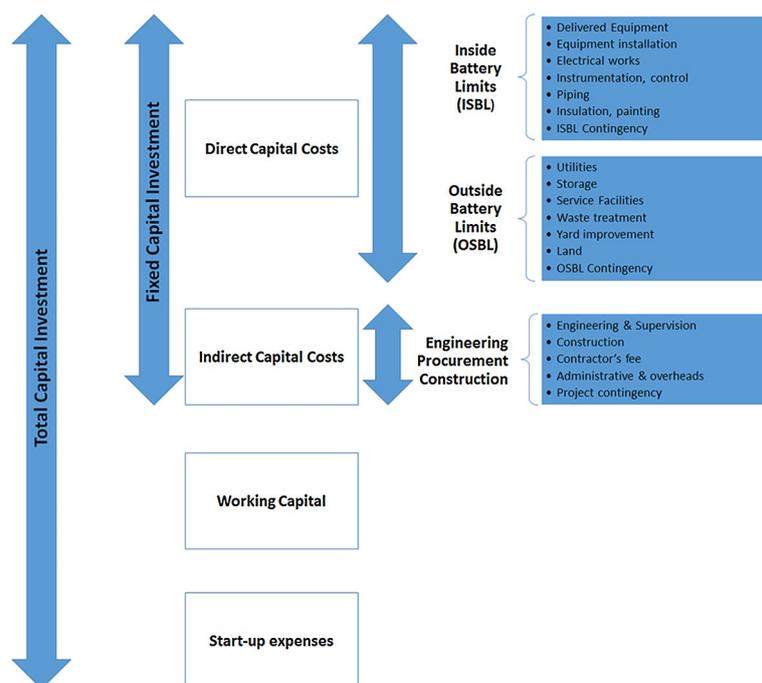


Figure 1. Total capital investment breakdown.

Table 1. Comparison of classification practices.^[6,12]

AACE std. ^[a]	ANSI std. Z94.0	ACostE ^[b]	TRLs ^[c]
Class 5 L: -20 to -50% H: +30 to +100%	OoM ^[d] -30/+50%	OoM ^[d] Class IV -30/+30%	TRL 1-4 technology conception, laboratory validation
Class 4 L: -15 to -30% H: +20 to +50%	Budget -15/+30%	Study Class III -20/+20%	TRL 5-6 technology validation & demonstration
Class 3 L: -10 to -20% H: +10 to +30%		Budget Class II -10/+10%	TRL 7 operational system demonstration
Class 2 L: -5 to -15% H: +5 to +20%	Definitive -5/+15%	Definitive Class I -5/+5%	TRL 8 system completion & qualification
Class 1 L: -3 to -10% H: +3 to +15%			TRL 9 actual system operation

[a] L = low, H = high. [b] ACostE = Association of Cost Engineers (UK). [c] TRL = technology readiness level. [d] OoM = order of magnitude.

(Figure 2). The overruns were more likely to occur if the scope was defined more poorly than Class 3 estimates.^[13] The sources of misestimation vary from failure in inflation projection, changes in scope and unpredictable events related to specific process characteristics resulting in cost growth. For pioneering plants, the cost growth is related to the use of new and unproven technology and to the high complexity of the process itself. Low process understanding explains why costing methods fail to accurately predict final capital costs.^[14] Hollmann described pioneering process plants as projects at the edge of chaos, which must be viewed as complex dynamic systems to understand their inherent risks and avoid disaster.^[15] The job of the estimator is quite preposterous because an overestimate can kill a project and put a career at risk, whereas an underestimate can lead to excess expenditure and plausible project withdrawal.^[13a] Both under- and overestimations tend to increase the final capital expenditure because an overestimate serves as a self-fulfilling prophecy and leads to ill-advised spending of capital resources. Only realistic estimates minimize final costs (Figure 3).^[16]

ing.^[12] TRL are matched to the corresponding class cost estimates in Table 1 to give an indication to researchers of the level of information needed.

Hollmann performed an analysis on the accuracy of cost estimates for over 1000 projects from the process industries (oil, gas, metal, chemicals etc.) He reported that the average or median overrun for large-scale process projects was 21%, whereas 10% of projects exceeded their budget by 70%

Biorefineries fall within the category of pioneering process plants because they employ new and unproven technology for commercialization, and thus, changes in scope and process design are almost unavoidable. In 2011, Range Biofuels filed for bankruptcy due to technology failure, leading to a loss of \$80 million of taxpayers' money.^[17] Similarly, KiOR, the first cellulosic biofuel plant, went into foreclosure in 2014 after unsuccessful operation of its manufacturing process on a commercial

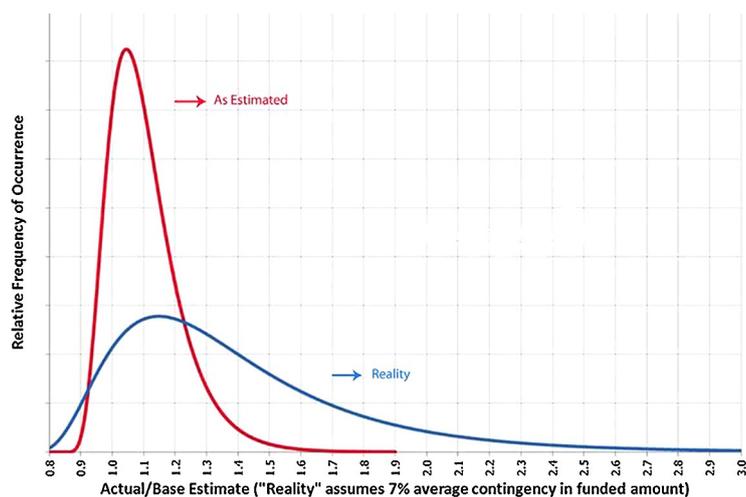


Figure 2. Actual chemical process industries estimate accuracy versus reality for typical large projects.^[13] Republished with permission from Chemical Engineering magazine.

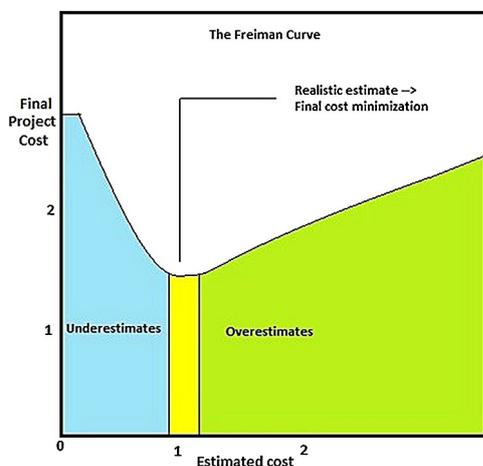


Figure 3. The Freiman curve for realistic estimates. Adapted from Ref [16].

scale.^[18] Thus, it is evident that the scaling up of biofuels and biochemicals production has imminent risks that can discourage public trust from the prospective of a viable biobased economy.

However, accurate capital cost appraisal and risk analysis, especially in the early stages, can offer realistic budgeting and prevent disaster.

1.2. Early capital estimates

Capital cost estimation methods are derived from process industries. These include not only the chemical or petrochemical industries, but also paper, sugar, manufacture of synthetic fibers, food industries,^[19] metal refining, petroleum refining, and power generation from fossil fuels.^[7] It can easily be assumed that the cost estimation methods also apply to biorefinery plants because they often resemble conventional processing units.

Early capital cost estimates, known as the ratio, seat-of-the-pants, guesstimate, or ballpark estimates,^[8] are vital but uncer-

tain due to the lack of information on the exact process configuration (low TRL), which explains the wide accuracy ranges in Table 1. However, Research and Development (R&D) engineers rely on conceptual estimates to decide on project viability and/or process alternatives. It is also at the start of a project that the company commits a large amount of capital to the new investment for a greenfield plant, a revamp, extension, or retrofitting of an existing facility. Conceptual estimates are crucial to pioneering plants for which the company has no previous experience and few or no similar plants exist. Ballpark estimates rely on escalation factors based on existing similar plants, equipment lists, or conceptual block diagrams indicating major process steps to predict capital costs. Three techniques are widely used for this purpose: 1) power law or exponential estimating, 2) factorial estimating, and 3) significant process step estimating.

1.2.1 Power law estimating

This technique is widely described/used in the literature because it allows extrapolation of cost data from one scale to another. Therefore, if historical data exists, the cost of a new plant can be estimated based on the total cost of a similar plant or parts of it. Because the cost depends on the size or scale of process equipment, the correlation given by Equation (1), first proposed by Williams,^[20] is often used:

$$\frac{C_1}{C_2} = \left(\frac{S_1}{S_2}\right)^p \cdot t \quad (1)$$

in which $C_{1,2}$ is the cost of an item at size or scale $S_{1,2}$ and p is an exponent that varies between 0.3 and 1.2, depending on the type of process/item being scaled. The exponent usually varies between 0.4 and 0.8 with an average value of 0.6; this is why Equation (1) is known as the six-tenths rule. Economies of scale appear when the exponent is less than one. The exponent tends to grow as the capacity increases until the maximum equipment capacity is reached. An exponent greater than one is an indication of negative economies of scale and most probably of multiple production lines (multistreaming) of the plant. Exponents for each type of equipment are published in the literature based on a large accumulation of data.^[7] The correction factor, t , is used to escalate data to the date and location of the estimation by using appropriate indices and correcting for differences in temperature, pressure, and materials of construction.^[7] Equipment cost correlations and graphs are found in various engineering handbooks as a function of capacity. Special attention should be paid to the range of use of the plots because the cost is often not a univariate expression, and technological progress and learning curves might not be taken into consideration.^[9a] In general, it is advisable not to use data that are more than ten years old (five when referring to total plant costs).^[8]

Table 2 presents value ranges of the exponent p for several common biorefinery types. We have been collecting capital

Table 2. Typical values of exponent p for common biorefineries.

p	Biorefinery types	Phase type ^[8]	Cost items (FOB) ^[a]
> 1.0			
0.9–1.0	seed crushing units	solids	multiple fermenters or other equipment items, catalysts, chemicals, civil works, construction
0.7–0.9	grains-to-bioethanol, lignocellulosic biomass-to-ethanol, renewable diesel, biomass-to-ethanol (by gasification)		crushers, compressors, electrostatic precipitators
0.6–0.7	oil-to-biodiesel	liquid	blowers, pumps, crystallizers, pressure vessels
0.3–0.6	–	gas	agitators, conveyors, dryers, filters, shell-tube heat exchangers, jacketed reactors, horizontal tanks

[a] FOB = free on board: cost at the manufacturing location.^[21]

cost data for various commercial biorefineries: curvilinear regression analysis of these data shows that grains-to-bioethanol, lignocellulosic biomass-to-ethanol, seeds crushing units, and thermochemically produced bioethanol plants do not follow strong economies of scale ($p \approx 0.75$ – 0.93) because they include extended solids pretreatment sections and/or multiple pieces of equipment operating in parallel. Furthermore, because most of them involve state-of-the-art technologies, scaling up requires unforeseen capital expenses (contingency), and thus, no learning curves apply on them yet. Some of these graphs are further studied in Section 3. Typical ranges of the exponent p for common pieces of equipment and plant components are also reported based on literature sources.^[21]

Because commercial biorefinery plants have only been emerging to a significant extent during the last decade, few historical data and cost information are publicly available. Companies are reluctant to publish cost data for their state-of-the-art technology and only publish information that will satisfy their shareholders' expectations and secure the next round of financing. As more biorefineries are announced to come online, more cost data will be made available, which will enable accurate precision of the exponent p .

1.2.2. Factorial estimating

The second category of cost methods is factorial estimating. Factorial estimates are based on the idea that all categories of capital expenditure in a plant are related to the cost of the purchased equipment. Thus, a detailed list of process equipment and its relevant cost have to be estimated either from literature data or vendors' quotes and then factors are applied to predict the capital investment. The most difficult part of this method is clearly the definition of the equipment list and its relevant purchased cost because, at the conceptual stages of a process, very little is known about specific equipment needs. Lang was the first to introduce the idea of factorial estimates by reporting that capital investment was related to the cost of

purchased equipment, with a factor f , the value of which depended on the type of process (fluids, solids, solids–fluids).^[22] Values for Lang's factors can be found in common engineering handbooks. The Lang factors have been improved and modified by various authors throughout the years; Hand, Wroth, Brown, Miller, Holland, Happel, Guthrie, Chilton, Hirsch and Glazier, Nishimura, Garrett, Chauvel et al., Brennan and Golonka, and Marouli and Maroulis are some of the authors who have proposed such types of methodologies.^[8,9,23] The latest report referring to factorial estimating, published by Woods, proposed a list of 500 pieces of equipment each with its own installation factor.^[24] Considering the amount of information and details required, factorial estimating is probably not suitable for conceptual estimates, but rather study or preliminary appraisals.

Researchers undertaking the design of a "conventional" biorefinery (such as a biodiesel plant), for which the majority of equipment is known, could preferably use factorial estimating, even for Class 5 (TRL 4) estimates. If the biorefinery under study involves state-of-the-art technology and complex equipment (such as for the production of biochemicals), for which neither literature cost data nor quotes from vendors are easily accessible, factorial estimating is more suitable for Classes 4 or 3 estimates (TRL 5–7), when project financing is probably already approved.

1.2.3. Significant process step estimating

Functional unit methods fall within the category of cost estimation relationships, which postulate the capital cost as a function of major process steps and parameters such as capacity, throughput, temperature (max/min), pressure (max/min), and construction materials. These methods are partially suitable for early-stage estimation because no detailed flowsheeting or equipment lists are usually necessary to calculate capital costs. The functional unit was first reported by Zevnik and Buchanan (1963); Gore (1969); Stallworthy (1970); Wilson (1971); Bridgewater (1976, 1981); Taylor (1977); Viola (1981); and Klumpar, Brown, and Fromme (1983), who collected historical plant data and attempted correlations.^[7,25] Each of the authors presented their own methodology for specific types of chemical processes, provided their definitions of the functional unit and proposed basic parameters that affected the costs. Special attention should be given to what part of the capital cost each method estimates, ISBL or fixed capital cost, because this misunderstanding is often the major source of miscalculations and errors in cost engineering.^[10a] It should also be noted that some of these methods are only suitable for study estimates because they require a high level of information. Details can be found extensively throughout the literature,^[8,23a,26] as well as in the Supporting Information. To the best of our knowledge, the last functional unit methods were proposed by Petley^[26] in 1997 and Chauvel et al.^[23a] in 2001.

There is a debate around the definition of the functional unit and all interested authors have attempted to give their

own interpretation. A general definition given by ChemE and the ACostE (2000) is as follows: "A functional unit is a significant step in a process and includes all equipment and ancillaries necessary for operation of that unit. Thus, the sum of the costs of all functional units in a process gives the total capital cost."^[6] Although cost methods based on functional units seem most appropriate for Class 5 biorefinery cost estimates (TRL 4), there are still two crucial points to keep in mind: the first one is, of course, the lack of historical cost data for reliable regression analysis, and the second is the redefinition of the functional unit to correspond to the process specifics of biorefineries and its ease of use for early estimations.

1.2.4. Thermodynamics estimating

Special mention is given to Lange's thermodynamics-based cost correlations that attempted to provide a simple tool for quick economic estimation by correlating the capital investment to the amount of energy lost in the process.^[27] The assumption is derived from the significant impact of heat losses on the total cost. To accommodate heat losses, dedicated equipment, and thus, dedicated costs are required. In both exo- and endothermic reactions, handling the heat of reaction requires larger surface areas for heat exchangers, which means increased capital costs. The author developed his method by correlating the energy losses of fuel manufacturing plants to the DCC and transfer duties of process segments to the ISBL costs. It is stated that these correlations are not a good indicator for small-scale, heat-neutral reactions or for batch processes used for manufacturing fine and specialty chemicals.

For biorefineries that include highly endo- and exothermic reactions, the correlations could produce accurate results. However, biorefineries often involve thermoneutral reactions for which the correlations are not recommended. Furthermore, energy consumption details are not often known during early-stage process development, and thus, do not allow the use of the correlation.

2. Early Capital Estimation of Biorefineries

All of the methods above could be applied, in principle, to calculate the capital costs of the biorefineries. Indeed, the methods have already been applied under the assumption that the regression models used in petrochemical processes could be extended to the emerging field of biorefineries. The majority of estimators rely on historical cost data from commercial biomass to chemicals/power plants. Still, few plants operate on a commercial scale while the costs and process data are not shared with the public. Over the past 10 years, there have been efforts to update costing methods in quick ways. Gallagher et al. suggested that capital costs typically increased less than proportionately with plant capacity in the dry mill ethanol industry in the USA and estimated a power factor of $p = 0.836$.^[28] Amigun and von Blottnitz proposed a cost-capacity factor of $p = 1.2$ for small- and medium-scale biogas installations in Africa.^[29] Crous^[30] combined factorial methods, such as those proposed by Guthrie, Miller and Peters et al.^[10a] to esti-

mate capital investment and decide on process alternatives. Costs for purchased equipment were derived from common engineering handbooks. Ereev and Patel developed the SCENT tool, which incorporated a detailed estimation methodology based on Woods' purchased equipment costs and factors for installation, direct and indirect costs proposed in the literature, and modified labor factors developed by the authors themselves.^[31] Claypool and Raman developed BioPET, which is a tool for estimating the major process steps found in downstream biochemical processes (fermentation, separation, catalytic stages, and purification) based on correlations for equipment sizing and power law estimating from costs reported in the literature.^[32] Finally, Piotrowski et al. reported a methodology based on Lange's thermodynamic approach.^[33] They proposed the estimation of the fixed capital investment based on the rated power of all pieces of equipment, which underestimates significantly the DCC because Lange's equation [Eq. (15), see below] is intended only for ISBL estimation.

Recent efforts by Cheali et al. attempted to specify the uncertainty of early cost models by using either the bootstrap parametric regression method when historical data was available or the Monte Carlo technique with expert judgement when no prior data was known.^[34] They reported large discrepancies in the results. Finally, Brown investigated the effect of two different factorial cost methods on the 20 year net present value (NPV) of several thermochemical routes to conclude that the choice of estimation method could change the NPV by up to \$300 million.^[35]

2.1. Work scope

Given the uncertainty around quick estimating, the authors decided to address the research hypothesis that different methods are (or not) consistent with each other, at least to a satisfactory degree. For this purpose, the current work assesses five functional unit methods that are approved and well known among estimators, as well as Lange's thermodynamic cost correlations. We escalated all selected methods to a common currency, location, and basis year. Three biorefinery processes, employing chemical, biochemical, and thermo-biochemical technologies, are used as validation models. We first compared the results with reference literature estimations and then with reported capital costs from commercial biorefineries. For the latter, cost information was retrieved from a large database we have been compiling with cost and process information for commercial biorefineries that are already in operation worldwide or are announced to come online in the near future.

2.2. Selected cost methods

The functional unit methods are Wilson's main plant item method; Taylor's process step scoring method; Bridgwater's correlations; Klumpar, Brown, and Fromme's process module method; and Petley's functional unit correlation (1997).^[25a-d, f, 26] They are all based on the principle that capital cost relates with plant size (S) through Equation (2):

$$\text{Capital Cost} = \text{Constant} \cdot S^P \quad (2)$$

Wilson studied 16 solid–fluid and fluid processing plants. His method first calculated the average unit cost (AUC) of the main plant items; a term referring to all principal equipment items other than pumps. Following Miller, he calculated the capital cost by using Equations (3) and (4):

$$\text{ISBL} = f_i N (\text{AUC}) F_m F_p F_T \quad (3)$$

$$\text{AUC} = 21V^{0.675} \quad (4)$$

in which ISBL is in pounds sterling (UK, 1971); f_i is an investment factor available from graphs with AUC; N is the number of plant items; AUC is the average unit cost; F_m is a parameter that correlates materials of construction, other than carbon steel; F_p and F_T are the correction factors for design pressure and temperature, respectively; and V is the average throughput in tons per year (tyr^{-1}). All factors can be calculated from graphs and scales reported in Wilson's paper. His method is suitable for process throughput between 10^4 and 10^6 tyr^{-1} , although it might produce erroneous results when no economies of scale apply.^[25a]

Taylor developed his method by analyzing cost data of 45 real plants built in the UK during the 1970s. His method relies on the idea that the cost of the plant is related to its capacity and to a complexity index expressing process and chemistry complexity by a relationship in the form of Equation (5):

$$\text{ISBL} = k_T \sum_1^N (1.3)^{CS} Q^{0.39} \quad (5)$$

in which ISBL is in millions of pounds sterling (UK, 1977); k_T is a constant equal to £0.042 million year per kiloton (yrkt^{-1}) for 1977; Q is the capacity in kilotons per year (ktyr^{-1}); N is the number of significant process steps (e.g., filter, react, distil); and CS is a complexity score determined for each process step to take account of factors, such as relative throughput, materials of construction, reaction time, storage time, temperature, pressure, multistreaming, and special conditions. The author reported a list of units that composed a process step and gave examples on the use of his method. The method can be used for capacities from 0.3 to 250 ktyr^{-1} , although it might not be suitable for processes with few process steps and/or appreciable level of solids handling.^[25d]

Bridgwater introduced various correlations in the late 1970s to 1980s. In 1976, he published Equation (6) based on the study of 24 plants from 16 hydrometallurgical extraction processes. He employed the traditional definition of the functional unit, not taking into account storage, pumping, heat exchanging, and multistreaming, although he considered the impact of mass throughput on the cost and the effects of weighed process pressure and temperature. He did not assess the effect of materials of construction.

$$\text{ISBL} = 37.7N \left(\frac{Q}{s^{0.5}} \right)^{0.85} \left(\frac{T_{\max} n}{N} \right)^{-0.17} \left(\frac{P_{\max} n'}{N} \right)^{0.14} \frac{\text{ENR}}{1300} \quad (6)$$

in which ISBL is in pounds sterling (UK, 1976); N is the number of functional units; Q is the plant capacity (tyr^{-1}); s is the process conversion; T_{\max} is the maximum temperature ($^{\circ}\text{C}$); P_{\max} the maximum pressure (atm); n and n' are the number of functional units operating at T and P greater than $T/2$ and $P/2$, respectively; and ENR is the Engineering News Record Construction Index (base 100 in 1913).^[25b]

In 1981, he presented similar equations for liquid and solid–liquid processes [Eq. (7), Eq. (8)]:

$$\text{ISBL} = 158N \left(\frac{Q}{s} \right)^{0.675} \frac{\text{PEI}(\text{UK})}{100}, \quad \frac{Q}{s} > 60000 \text{t yr}^{-1} \quad (7)$$

$$\text{ISBL} = 13850N \left(\frac{Q}{s} \right)^{0.3} \frac{\text{PEI}(\text{UK})}{100}, \quad \frac{Q}{s} < 60000 \text{t yr}^{-1} \quad (8)$$

He also proposed a linear correlation in the form of Equation (9):

$$\text{ISBL} = \left[401600 + 1.304 \left(\frac{Q}{s} \right) \right] N \left[\frac{\text{PEI}(\text{UK})}{100} \right] \quad (9)$$

Finally, by including the effects of pressure and temperature, he proposed Equation (10):

$$\text{ISBL} = 193N \left(\frac{Q}{s} \right)^{0.665} e^{2.58 \cdot 10^{-7} Q T_{\max}^{-0.022} P_{\max}^{-0.064}} \left[\frac{\text{PEI}(\text{UK})}{100} \right] \quad (10)$$

In Equations (7)–(10), ISBL is in pounds sterling and PEI is the Process Economics International Cost Index for the UK (base 100 in 1975). He reported a $\pm 20\%$ deviation for all correlations.^[25c]

Klumpar et al.^[25f] introduced the process module method based on a list of 20 plants consisting of solid, liquid, and gas processes from natural resource extraction technologies. They defined 12 process modules thoroughly according to the main physical parameter being changed, such as temperature, pressure, and number of streams, and thus, classified the main equipment items to one of these categories. In the end, each process module consisted of the main equipment item and its auxiliary units. Their method accounted for multistreaming and storage and they proposed Equation (11):

$$\text{ISBL} = k_k F N Q \quad (11)$$

in which the ISBL is in dollars (US, 1981), α is equal to 0.57, k_k is a constant equal to $\$180 \text{ h kg}^{-1}$, Q is the capacity (kg h^{-1}), N is the number of process modules, and F is a function of maximum temperature and pressure. The authors claimed that their method was suitable for a broad range of processes and capacities.

Furthermore, they improved Equation (11) by assuming a variable exponent, ν , as a function of module distribution, x_i [Eq. (12)]:

$$\nu = \sum_{i=1}^{12} c_i x_i \quad (12)$$

in which constants (c_i) for x_6 , x_7 , and x_{10} were found equal to zero. They reported an accuracy of $\pm 30\%$ for 94% of validation processes.^[25f]

Petley worked on 79 processes and proposed variations of existing rapid methods, while introducing new parameters, such as workforce and number of reactions critical to the capital cost. He also reported Equation (13) by correlating the number of functional units, capacity, temperature/pressure maximum, and materials of construction correction factor to estimate ISBL in US dollars (West Germany, 1988).^[26]

$$\text{ISBL} = 55882Q^{0.44} N^{0.486} T_{\max}^{-0.038} P_{\max}^{-0.02} F_m^{0.341} \quad (13)$$

Finally, Lange's cost correlations based on thermodynamics are also used for the purposes of our study. He proposed Equation (14), which correlated DCC with the amount of energy losses:

$$\text{DCC} = 3.0 \bullet (\text{energy losses [MW]})^{0.84} \quad (14)$$

He also reported Equation (15) by correlating the total installed cost of process segments, such as feed preheating, reactor heating/cooling, and distillation segments, with their corresponding transfer duties.

$$\text{ISBL} = 2.9 \bullet (\text{energy transfer [MW]})^{0.55} \quad (15)$$

in which DCC and ISBL are in millions of US dollars (1993) and energy losses and energy transfer are in MW.^[27]

2.3. Selected cost basis

Variations of the correlations' constants have been proposed in the literature,^[8,26] but since recorelation details are unknown, we used the original equations as proposed by their authors and escalated them according to their instructions. First, we set 2011 as the common cost basis year and calculated the ISBL in millions of dollars for a greenfield plant built overnight in the US (Gulf Coast). We compared the six proposed methods with the reported literature estimations. Then, we calculated the DCC in millions of US dollars for all processes to compare the results obtained by the methods with announced commercial plant costs retrieved from our database. We report details on the escalation methodology and calculations for updating the aforementioned methods in the Supporting Information.^[8,36]

2.4. Selected case studies

We selected three biorefineries to assess the reliability of the estimation methods under study: 1) ethanol production by corn dry milling, 2) biodiesel production by soybean oil transesterification, and c) ethanol production by indirectly heated biomass gasification. The first two employ widely known technologies and are the most common biochemical and chemical biorefinery processes, respectively. Many commercial plants operate at a large scale around the world, some of which have made their capital investment known to the public, and thus, we were able to evaluate the precision of the results for each method. The third process involves state-of-the-art technology because it combines thermochemical (gasification) and biochemical (syngas fermentation) routes for ethanol production. Because there are only a few such commercial plants, this process is used to test the reliability of the cost methods in accurately predicting capital costs of pioneering biorefinery projects. The validation processes represent the three broad process technologies employed in biorefineries: biochemical, chemical, and thermochemical. For most accurate application of the methods, we used detailed flowsheets involving rigorous material and energy balances for all processes; these are reported in the Supporting Information.

The corn to ethanol model used is the one developed by Kwiatkowski et al. for a 119 ktyr⁻¹ ethanol and 130 ktyr⁻¹ dried distillers grains soluble production capacity plant.^[37] The biodiesel model is based on the work of Haas et al. for an annual production capacity of 33 kt.^[38] Both of them are widely cited, and therefore, are considered a reliable source of information. The detailed flowsheets were developed on SuperPro[®] Designer and are available from Intelligen, Inc. The biomass gasification to ethanol process flowsheet for a plant capacity of 33 ktyr⁻¹ was developed on Aspen Plus[®] by some of the authors^[39] and is based on the reports prepared by Jeffery (personal communication). All processes handle solid-liquid systems (apart from syngas ethanol, for which there is also a dominant gas phase) and fall within the application ranges of the selected methods.

3. Results and Discussion

3.1. Deterministic comparison with reference literature estimates

Careful application of the selected methods provides the results presented in Table 3.

We compared the results obtained from the capital estimation methods with the reference costs from the corresponding studies (Table 3, reference ISBL). For the corn-to-ethanol process, Lange [Eq. (15)], Petley, and Klumpar (A) give the best predictions by overestimating the ISBL by 14, 18, and 31%, respectively. Klumpar (A) overestimates the ISBL for the biodiesel plant by 36% and Lange [Eq. (15)] underestimates it by 34%. Lange [Eq. (15)], Petley, and Taylor approximate the thermochemical ethanol process satisfactorily, with deviations of -19, 17, and 22%, respectively. The smallest deviations are observed

Table 3. Comparison of ISBL costs.

Product	Bioethanol (119 kt _{yr} ⁻¹)	Biodiesel (33 kt _{yr} ⁻¹)	Syngas ethanol (33 kt _{yr} ⁻¹)
	ISBL cost (millions of US\$, 2011; US)		
Wilson	266	21	201
Taylor	105	24	106
Bridgwater (A)	176	25	126
Bridgwater (B)	192	30	170
Bridgwater (C)	222	41	185
Bridgwater (D)	214	19	176
Klumpar et al. (A)	78	13	150
Klumpar et al. (B)	172	84	2738
Petley	70	39	102
Lange [Eq. (15)]	68	6	70
reference	59 ^[37]	9 ^[38]	87 ^[40]

for thermochemical ethanol and the largest for biochemical ethanol. Almost all methods tend to overestimate the actual ISBL of the biorefinery models. Lange [Eq. (15)] provides for the smallest deviations among the methods for all three case studies (+14, -34, -19%), followed by Klumpar (A) (+31, +36, +72%), and Taylor (+77, +152, +22%).

3.2. Probabilistic comparison with commercial capital costs

However, as the reference costs are only estimations, their accuracy has to be verified. We have been compiling a database with historical costs and process parameters from existing or announced biorefineries worldwide. The information is collected mainly from press releases and announcements published by the companies. To date, the database has gathered information for 320 commercial biorefineries employing all kinds of technologies to produce biofuels and/or biochemicals. We retrieved capital cost data for dry corn to ethanol, soybean oil to biodiesel, and thermochemical ethanol production plants; these are illustrated as scatterplots in Figures 4–6 (marked as circles). It is assumed that the announced commercial capital cost refers to the total DCC of the plant, that is, ISBL + OSBL, if no further information is provided. It should be noted that not all plants are greenfield projects: some are colocated or additions to existing plants and some are site expansions, which means that the OSBL (offsites) values are expected to vary according to site specifics. For a greenfield plant, under ideal conditions, the OSBL makes up 24–50% of the ISBL.^[10a] By assuming a logarithmic relationship between the cost and capacity, we drew the 90% confidence intervals (C.I.) around the best-fit linear curve.^[41] According to data in Figure 4, the median corn-to-ethanol plant operates at a capacity of 189 kt_{yr}⁻¹ with a respective capital cost of \$143 million (in 2011; \$120 and 171 million, 90% C.I.), that is, \$757 per ton of installed capacity (\$635 and 905 per ton, that is, -16, +20, 90% C.I.). Unfortunately, the reference plant is designed for a production capacity of 119 kt_{yr}⁻¹ and very few data are found for plants of a similar size. The same applies to the soybean oil biodiesel process, whereas the median biodiesel plant operates at 200 kt_{yr}⁻¹ with a capital cost of \$93 million (in 2011; \$72 and 119 million, 90% C.I.), that is, \$465 per ton (\$360

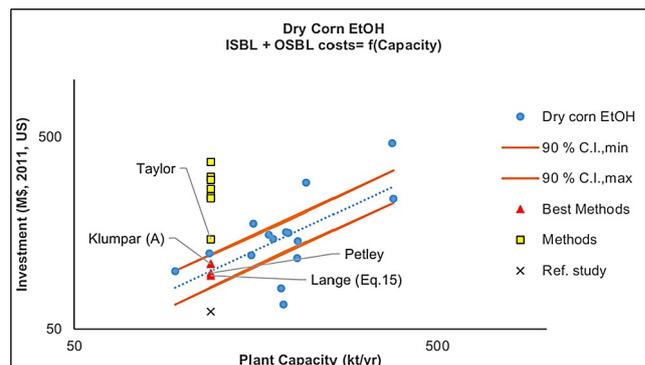


Figure 4. Corn-to-ethanol biorefineries: ISBL + OSBL costs (millions of \$, 2011, US) versus plant capacity [kt_{yr}⁻¹].

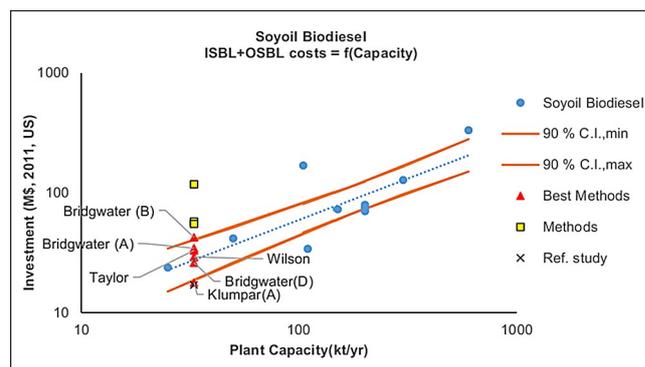


Figure 5. Soybean oil biodiesel biorefineries: ISBL + OSBL costs (millions of \$, 2011, US) versus plant capacity [kt_{yr}⁻¹].

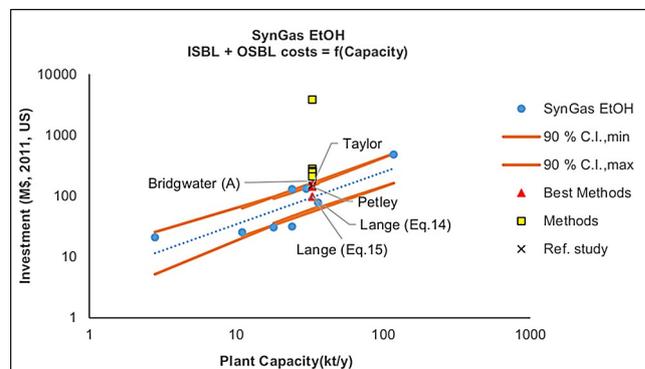


Figure 6. Thermochemical ethanol biorefineries: ISBL + OSBL costs (millions of \$, 2011, US) versus plant capacity [kt_{yr}⁻¹].

and 595 per ton, that is, -23, +28, 90% C.I.; Figure 5). On the other hand, only a few thermochemical ethanol commercial plants exist and report a median plant cost of \$73 million (2011) for an ethanol production of 24 kt_{yr}⁻¹ (in 2011; \$47 and 114 million, 90% C.I.), that is, \$3042 per ton of installed capacity (\$1958 and 4750 ton, that is, -36, +56, 90% C.I.; Figure 6). We performed similar analyses for second-generation ethanol production plants, which reported a median capital cost of \$2899 per ton (\$2395 and 3509 per ton, that is, -17, +21, 90% C.I.) The median oil seeds crushing unit-to-biodiesel pro-

duction plant reported a capital expenditure of \$751 per ton (\$538 and 1047 per ton, that is, -28 , $+39$, 90% C.I.), whereas the median renewable diesel retrofit plant operated at \$589 per ton (\$402 and 865 per ton, that is, -32 , $+47$, 90% C.I.).

The total DCC estimations provided by the reference studies are shown at the bottom of Table 4 (reference). The authors stated that the total capital cost for the corn to ethanol pro-

Table 4. Comparison of DCC.

Product	Bioethanol (119 kt yr ⁻¹) Direct costs (ISBL + OSBL; millions of US\$; 2011, US)	Biodiesel (33 kt yr ⁻¹)	Syngas ethanol (33 kt yr ⁻¹)
Wilson	372	29	281
Taylor	147	33	148
Bridgwater (A)	246	34	176
Bridgwater (B)	269	42	238
Bridgwater (C)	311	57	259
Bridgwater (D)	300	26	246
Klumpar et al. (A)	109	18	209
Klumpar et al. (B)	241	118	3833
Petley	98	55	142
Lange [Eq. (15)]	95	9	98
Lange [Eq. (14)]	31	0.9	97
reference	61 ^[37]	17 ^[38]	149 ^[40]

cess included only wastewater treatment and air-handling facility costs, whereas for the biodiesel process the total capital cost included the loading/unloading station, utility systems, and yard improvements. Therefore, the OSBL for these two processes are expected to be underestimated. The OSBL of thermochemical ethanol include the utilities and storage, the services, and the waste treatment facilities, and thus, the DCC is satisfactorily calculated. The reference literature estimations, shown in Figures 4–6 (marked with crosses), fall outside the 90% C.I. for corn to ethanol, just below the minimum 90% C.I. for biodiesel, and on the maximum 90% C.I. for the thermochemical ethanol production plant; thus confirming the aforementioned assumption.

To compare the results of the costing methods, we escalated the ISBL costs to DCC (ISBL + OSBL). We added 40% to the calculated values in Table 3 to account for the OSBL (or offsites) for all cost methods (assuming ideal conditions for a greenfield chemical plant,^[10a] since no specific information on biorefineries' offsites has been reported yet in the literature). We also used Equation (14), proposed by Lange, because it already estimated DCC. The updated results for the cost estimation methods are given in Table 4.

The results in Table 4 are also plotted on Figures 4–6. The methods that fall within the 90% C.I. are marked as triangles, whereas those that fall outside are marked as squares. For the corn-to-ethanol plants, there are many data points that are not strongly correlated, whereas the biodiesel plants show a clear trend. There are some data points for the thermochemical ethanol process, which are also strongly correlated. Correlations by Klumpar (A), Petley, and Lange [Eq. (15)] fall within the 90% C.I. of the corn-to-ethanol process, whereas those of Wilson; Taylor; Bridgwater (A), (B), and (D); and Klumpar (A) satisfy the

limits of the biodiesel plants. Taylor, Bridgwater (A), Petley, and Lange [Eqs. (14) and (15)] provide accurate estimations within the 90% C.I. of the thermochemical ethanol biorefineries.

Because the corn-to-ethanol and biodiesel validation processes are designed for production capacities of 119 and 33 kt yr⁻¹, no conclusions can be drawn regarding the performance of cost methods for such processes operating at median commercial capacity. Therefore, we decided to scale up both processes to 200 kt yr⁻¹ and reapply the cost methods. The scaled up process flowsheets on SuperPro[®] were prepared and provided by Intelligen, Inc. We compared, once again, the DCC estimations of the cost methods with DCC values reported for commercial plants. For biochemical ethanol, Klumpar (A), Petley, and Lange [Eq. (15)] fell within the 90% C.I., as they did for the smaller capacity. However, for the soybean oil biodiesel process, the performance of the methods slightly changed: Taylor; Bridgwater (B), (C), and (D); and Petley fell within the 90% C.I. (All relevant figures can be found in the Supporting Information.)

3.3. Discussion of results

In this study, we performed two types of comparison: the first involved a deterministic comparison between the ISBL cost, as calculated from the costing methods, and the ISBL reported in the reference literature. The second involved a preliminary statistical comparison of the methods' estimates for the DCC with reported cost data from commercial biorefineries. For the corn-to-ethanol plants, Lange, Petley, and Klumpar (A) provided accurate predictions for the deterministic and probabilistic comparison (for both 119 and 200 kt yr⁻¹). The reference literature estimate does not widely underestimate the cost either. Apparently, the ISBL estimations reported in literature are consistent with the real ISBL costs of the commercial plants. For the deterministic comparison of the biodiesel model, Klumpar (A) and Lange [Eq. (15)] provided the best ISBL estimate, whereas correlations by Wilson; Taylor; Bridgwater (A), (B), and (D), and Klumpar (A) fell within the 90% C.I. of the data for commercial plants. However, at an operating capacity of 200 kt yr⁻¹, Taylor; Bridgwater (B), (C), and (D); and Petley provided the best estimates. Because the results do not concur, we suggest that capital cost estimations for biodiesel processes are compared with numerous strongly correlated commercial plant data. For the deterministic comparison of the thermochemical ethanol plants, Lange [Eq. (15)], Petley, and Taylor provided the best appraisals, although Taylor, Bridgwater (A), Petley, and Lange [Eqs. (14) and (15)] also fell within the 90% C.I., and thus, the results confirmed the assumption that the capital cost estimates were consistent with the actual costs.

In general, the largest deviations were reported for the bioethanol process. Almost all methods overestimated its actual cost; Wilson explicitly stated that his method might not be valid for such a process, whereas the methods of Klumpar and Taylor satisfactorily approximated the cost because they took into account multistreaming and reaction time. The accuracy of Klumpar (A) was also because this method was developed based on natural source extraction processes, which involved

solids grinding. Taylor's deviations were due to extensive corn handling involved in the process; this method was not primarily developed for such processes. Furthermore, the method put a high weight on step relative throughput and, given the high water usage, it led to slight overestimates. Petley's result was also quite accurate: it could not be attributed to the inherent assumptions of the correlation, but to the large process database from which it was derived. All Bridgwater's correlations deviated significantly from the reported DCC for attributing high scores to the process conversion. For the bioethanol process, this is rather small, once again due to high amounts of solvent, and according to Bridgwater, this makes the process more complex and more expensive. Lange's [Eq. (15)] correlation for the ISBL provided a very good appraisal because the costs of distillation and purification were quite high, and thus, the amount of energy transfer was strongly correlated to the cost. As expected, Lange's [Eq. (14)] correlation for the DCC was not as accurate because no highly endo-/exothermic reactions were involved in the process and the plant scale was rather small, involving both continuous (distillation columns) and batch units (fermenters). The DCC and capacity of the corn-to-ethanol plants are (not strongly) correlated, but do not follow strong economies of scale.

For the biodiesel process, the majority of methods fell within the 90% C.I.: the reported deviations can be explained by the impact of temperature on the total capital cost. The cost was overestimated because of the weight given to the maximum process temperature. The methods were developed during the 1970s and, since then, there has been technical progress to reduce the cost of the pieces of equipment versus their operating temperature. It is evident from the results in Figure 5 that biodiesel plants fall within the category of conventional chemical plants and follow strong economies of scale.

The smallest deviations were reported for thermochemical ethanol. The main reason is that this process is quite similar to the classic coal gasification process, which is probably part of the costing methods' database. Furthermore, its syngas fermentation part is quite small and similar to a loop reactor or a gas bubble column (typical equipment in chemical processes), and thus, its negative economies of scale do not interfere with the integrity of the methods. It should be kept in mind that the syngas fermentation part involves state-of-the-art technology, which might cause scaling up bottlenecks, requiring extra capital expenses, as has recently been the case for INEOS technologies with high levels of hydrogen cyanide impeding fermentation reactions and requiring additional scrubbers.^[42] Thermochemical ethanol biorefineries are strongly correlated and do not follow strong economies of scale.

As mentioned previously, the methods of Lange [Eq. (15)] and Klumpar (A) provided the highest accuracy for all case studies in the deterministic comparison. For the probabilistic comparison, Taylor's method provided the least deviations for all three processes at 119, 33, and 33 ktyr⁻¹, respectively, whereas Petley was the most accurate for all biorefineries on a commercial scale.

If some of these methods were to be used for budgeting purposes, their range of applicability and ease-of-use have to be reviewed. Taylor's method gave very good overall results: it employed not only the capacity, but also the relative throughput, which took into account water usage as an indicator of plant size, and thus, of capital cost. Reaction time is taken into account as a crucial parameter that affects the cost of batch processes. Significant process steps are thoroughly explained and multistreaming is taken into consideration. However, multistreaming, along with other parameters, such as storage time or materials of construction, are unlikely to be known in the early conceptual phase. Its estimation deviations are due to its invalidity for estimating large-scale solids handling processes. Klumpar (A) was accurate because it also took into account module throughput, but required full knowledge of the equipment needed to build the plant, along with its mass balances. Therefore, the use of Taylor's and Klumpar (A) as Class 5 (TRL 1–4) estimating methods is questionable because they are more likely to be used for Class 4 (TRL 5) and Class 3 (TRL 7) estimates, respectively. Petley's correlation estimated satisfactorily biochemical and thermochemical ethanol, as well as the 200 ktyr⁻¹ biodiesel process; it is a quite simple method to use, and thus, suitable for Class 5 estimates or TRL 4. Its high accuracy, despite its simplicity, is attributed to the large number of processes the author used to develop his method. Furthermore, it is the most recent of the cost methods. Wilson's method provided mediocre results, required a high level of detail (Class 3 or TRL 7) and it was not suitable for processes that did not follow economies of scale (such as biochemical biorefineries). Bridgwater's correlations were quite accurate for the biodiesel process, but they generally failed to correctly estimate the other processes. They are suitable for Class 5 estimates or TRL 4. The most disappointing results were given by Klumpar (B), which gave estimates with more than 180% deviation. Finally, Lange's thermodynamic cost correlations were used as an attempt to investigate their applicability on biorefinery processes. Equation (15) provided quite accurate results for biochemical and thermochemical ethanol due to the purification complexity of the former and the cooling demands of the latter. As the author also suggested, this correlation might not be suitable for early estimations because it demanded at least a first level of process design; thus, it is suitable for Class 4 or TRL 6. Equation (14) provided quite accurate results for thermochemical ethanol, whereas it produced rather disappointing results for the other two processes by greatly underestimating their costs. This was in accordance with Lange's remarks regarding the applicability of his correlation, namely, that it was not suitable for small-scale processes involving thermoneutral reactions or batch units. Indeed, the total heat losses for the biodiesel process are outside the range of applicability of the correlation because this is not an energy-intensive process. The corn-to-ethanol process involves a large section of solids handling, for which the correlation cannot provide estimates because it comes from a regression analysis of gas–liquid processes. Equation (14) is appropriate for Class 5 estimates or TRL 4.

Although all methods entail a correct approach towards estimation, extrapolation to pioneering biorefinery processes must be applied with caution. The majority of techniques date back to the 1970s or 1980s, so retrieving suitable escalation factors is not only challenging and time consuming, but also introduces inevitable errors and deviations. In the present study, some methods' results are satisfactory for estimations at $-50/+100\%$ uncertainty, but this depends on the amount of available process data. Special attention should be paid to the use of the methods on biorefineries involving state-of-the-art technologies because no learning curves apply to them yet. We encourage researchers to recalculate the constants of the methods based on current process and cost data for the capital estimation of future biorefineries. Finally, we recommend the use of Taylor's method for Class 4 or TRL 5 because it provides the most accurate results among the methods for all types of biorefineries, reporting an average accuracy of $+73\%$ for the biochemical, -5% for the chemical, and $+55\%$ for the thermochemical biorefinery. Lange's Equation (15) is recommended for TRL 6, with -9% accuracy for the biochemical, $+70\%$ for the chemical, and $+3\%$ for the thermochemical process. For Class 5 estimates or TRL 4, Petley's correlation provides an average accuracy of -4% for the biochemical, $+67\%$ for the chemical, and $+49\%$ for the thermochemical biorefinery. We also suggest that budgeting of future biorefineries should also rely on reported capital costs of existing biorefineries, rather than on sole literature estimations or cost correlations, whenever possible.

4. Summary and Outlook

As numerous biorefineries are lined up for commercial scale, there is a strong incentive to amend and improve shortcut cost models to ensure correct budgeting for successful project commercialization. For early-stage estimations, existing shortcut cost methods make valuable paradigms of methodologies, saving significant effort in scaling up biorefinery plants (Taylor, Klumpar (A), Petley, Lange). However, they often render cost estimates that are questionable at times because the processes used to tune those methods mostly relate to conventional chemical plants and not biorefineries (Klumpar (B)). This study reports that, currently, the median unit capital cost is \$757 per ton for a dry corn mill ethanol plant, whereas it is \$2899 per ton for a lignocellulosic and \$3042 per ton for a thermochemical ethanol production biorefinery. The median oil-to-biodiesel plant has a capital expenditure of \$465 per ton, whereas the median seeds crushing-to-biodiesel plant operates at \$751 per ton and the renewable diesel retrofit plant at \$589 per ton. Cost estimates in biorefineries follow similar patterns to those of conventional process plants. However, they hold several differentiating attributes, as well as different weights through which cost is distributed in the plant. Such attributes require a shift of the bias of analysis for strictly biorefinery processes to develop power factors and significant process steps methods that are suitable for early-stage estimation.

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Keywords: biomass · early-stage estimates · investments · process development · sustainable chemistry

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