Assessing the future of second-generation bioethanol by 2030 : a techno-economic assessment integrating technology learning curves

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ABSTRACT

Lignocellulosic biomass is the most abundant source of renewable biomass and is seen as a high-potential replacement for petroleum-based resources. The conversion technologies to advanced biofuels are still at a low maturity level, thus allowing for future cost reductions through technological learning. This fact is barely considered in state-of-the-art techno-economic assessments and a structured approach to account for technological learning in techno-economic assessments is needed. In this study, a framework for techno-economic assessments of advanced biofuels, integrating learning curves, is proposed. As a validation of this framework, the economic feasibility of the valorization of corn stover for the production of second-generation bioethanol in Belgium is studied. Process flowsheet simulations in Aspen Plus are developed, with an emphasis on the comparison of four different pretreatment technologies and two plant capacities at 156 dry kt biomass/y and 667 dry kt/y. The dilute acid pretreatment model of the large-scale biorefinery required the lowest minimum learning rate to reach an economically feasible biorefinery by 2030, being 3.9%, almost half as the one calculated for the smaller scale plant. This learning rate seems to be achievable based on learning rates commonly estimated in literature. We conclude that there is a potential for advanced ethanol production in Belgium under the current state of technology for large-scale

biorefineries, which require additional biomass imports, when accounting for future cost reductions through learning.

KEYWORDS

Lignocellulosic biomass, advanced biofuels, pretreatment, learning rate

1. INTRODUCTION

Worldwide concerns over the high energy consumption and greenhouse gas emissions leading to climate change, have shifted the interest from fossil fuels to renewable energy sources [1]. Notably, the transport sector was responsible for around 27% of the total global greenhouse gas emissions in 2019 [2]. The second revision of the EU Directive 2018/2001 (RED III) has set new goals for renewable energy in the European Union by 2030, aiming at having at least a 45% share of renewable energy in the overall energy consumption [3]. At least 14% of the total energy required for the transport sector should be derived from renewable sources, while advanced biofuels should make a contribution of at least 3.5% [4].

Advanced biofuels are biofuels produced from renewable sources as described in the Part A of the Annex IX of the EU Directive 2018/2001 [4]. These can be further classified into second-generation biofuels, which are produced from agricultural/forestry residues, waste or non-food crops [5]. In Europe, there were 26 biorefineries commercially producing liquid biofuels in 2021, with 31% of those using secondary biomass (e.g., residues from agriculture, forestry and other organic residues/wastes) as feedstock, while the rest using crop-based feedstock (e.g., starch, corn and sugar) [6]. However, competition with the food supply chain may lead to land use changes and food price increase [7], although this has been limited over the past years within the EU [8]. Also, in case of geopolitical conflicts and global pandemics, food security concerns may rise. Thus, second-generation biofuels production seems to be pivotal.

Lignocellulosic biomass is a promising renewable feedstock due to its abundance and low cost. Its composition mainly consists of cellulose, hemicellulose and lignin [9]. Two primary conversion pathways of lignocellulosic biomass to biofuels exist: the biochemical, whose main product is bioethanol, and the thermochemical, whose main products are biodiesel and bio-jet fuels [10]. The biochemical pathway requires an extra processing step, known as pretreatment, prior to saccharification and fermentation, due to the complex and heterogenous structure of lignocellulose, in order to achieve a better enzyme accessibility to the polysaccharides. Pretreatment is a critical step for the economic feasibility of a biorefinery, as it plays a vital role in the final fuel yield [9].

In 2021, EU was the largest biodiesel producer with numerous large-scale plants already at a Technological Readiness Level (TRL) of 9 [11,12]. On the other hand, remarkable efforts have been made to improve pretreatment processes over the years and therefore second-generation ethanol production. Despite these efforts, the commercialization of second-generation ethanol production still remains a challenge, mainly due to the costs associated with the pretreatment process. Indeed, only 1% of the total bioethanol production within the EU in

2021 was produced from lignocellulosic biomass [12]. Currently, biochemical conversion of lignocellulosic biomass to ethanol is still at a TRL 7-8, with only few plants that have reached an early commercial case [11].

The first commercial plants of a specific technology have still the potential of decreasing their production costs in the future. These are often called first-of-a-kind (FOAK) technologies, while the mature ones are called nth-of-a-kind (NOAK) [13]. This cost reduction can be induced by technological learning, which is assumed to improve the performance of the new technology by gaining more experience. Technological learning and cost reductions are usually associated with the learning curve approach, in which cost reductions are considered as learning effects. Specifically, this theory assumes that the technological costs are decreased over time per doubling of cumulative production under a specific learning rate [14].

T.P. Wright developed the learning curve concept based on his observations on the reduction of labor costs in aircraft industry, due to the increase of cumulative production [15]. This concept was later extended to describe the relationship between the decrease in production cost and the cumulative production volume in various industries, mainly in the energy sector. Solar photovoltaic systems and wind turbines have been thoroughly studied in literature, while fewer studies have been conducted in the field of fossil-fuel and bioenergy plants [14]. The experience curve is another concept, introduced by the Boston Consultancy Group in 1968, to describe the decrease in total production cost as a function of increasing cumulative production [16]. Both terms are used interchangeably in the literature, but initially had different meanings.

The main difference is that the learning curve focuses on the reduction of the labor cost, while the experience curve illustrates the decrease in the total production cost. For consistency reasons with the literature, we use the term learning curve to cover both in the present study.

A recently published review by Thomassen et al. [17] on learning curves applied in energy technology assessments, indicated that 66% of the investigated studies (80 studies in total) calculated learning effects based on (i) estimations from literature data, (ii) estimations from a similar technology and (iii) rules-of-thumb according to the maturity of the studied technology. On the other hand, the calculation of learning effects is typically based on historical data extrapolated to the future. As far as advanced biofuels production is concerned, there have been some attempts to account for learning effects in future cost projections. However, due to the lack of historical data for such emerging technologies, most of the available studies are estimating learning rates based on the maturity of the investigated technology [18–22]. Moreover, Mustapha et al. [23] and Chen et al. [24] estimated learning rates on second-generation biofuels based on literature data for similar technologies, while Lee et al. [25] used a photovoltaic technology learning rate for biobutanol and algal biofuels production.

Given the increased need for advanced biofuels in EU, according to the revised EU Directive 2018/2001 [3], learning effects could be observed as the cumulative production grows. Therefore, learning curves can be applied to study potential future cost reductions on the biochemical production of bioethanol from lignocellulosic biomass, as this technology is currently limited because of high production costs. Due to the lack of historical data on advanced biofuels production as well as the uncertainty surrounding the choice of learning rates based on technological maturity and similar technologies, an innovative calculation approach is suggested in order to identify if an emerging energy technology is likely to reach commercial viability, based on the concept of learning curves.

In this study, we propose a novel learning curve-based calculation method to account for potential future cost reductions by learning effects in techno-economic assessments (TEA). The method is applied to the case of bioethanol production from corn stover in Belgium. Two different biorefinery capacities are investigated: (i) using only the domestically produced corn stover as feedstock and (ii) importing additional feedstock. Due to the importance and complexity of the pretreatment process, four common methods, namely dilute acid, alkaline, steam explosion and liquid hot water are studied, process simulation models are developed and a comparative economic assessment is conducted. These pretreatment methods are chosen as the most mature and suitable for the biochemical conversion pathway [26,27]. Despite the fact that the studied biorefinery includes some systems that are mature and have reached the NOAK stage, the use of new technologies, such as the pretreatment, is enough to consider the plant as FOAK [13].

An overview is given on learning curves, along with definitions, and a method is presented to fill the gap in literature for advanced biofuels production technology. The focus is given on two different single-factor learning curves, the single- and multi-component learning curves. An economic assessment is performed, followed by a break-even point analysis, which calculates the cost reduction needed to reach a profitable investment (i.e. Net Present Value (NPV) equal to zero) in the future. According to the required cost reductions, learning rates are calculated. This approach levels the playing field, allowing for fewer assumptions and therefore miscalculations compared to the commonly applied calculation methods mentioned above. Simultaneously, a comparison with the literature for similar technologies is possible, indicating the feasibility of this biorefinery plant in the future. As a result, this study investigates the economic feasibility of a commercial second-generation bioethanol plant in Belgium and explores its future prospects, induced by technology learning.

2. MATERIAL AND METHODS

In the proposed methodology, a workflow is provided to integrate learning effects calculation (dashed lines in **Fig.1**) in the conventional TEA framework (full lines in **Fig.1**). The first step is the scope definition. Then, the TEA methodology described by Van Dael et al. [28] is applied, with an addition of learning curves. The TEA methodology starts with the market study (within the geographical areas described in the scope definition), investigating market parameters, such as commodity prices and volumes, affecting the commercialization of the biorefinery project and a process flow diagram is developed along with mass and energy balance calculations. A base case economic assessment is then applied, estimating the economic viability based on technical and economic criteria. This step focuses on a comparative assessment of bioethanol plants in Belgium with different capacities and pretreatment processes. The cost reduction required to reach a profitable investment is calculated in this stage. The addition of the learning curves concept in the existing TEA methodology includes first a detailed definition of the applied learning curves, where different approaches for the multi-component learning curve are discussed. In the following step, the minimum learning rates required for the desired cost reduction are calculated for two different learning curves. Finally, the results are interpreted and compared with data from relevant studies in literature.

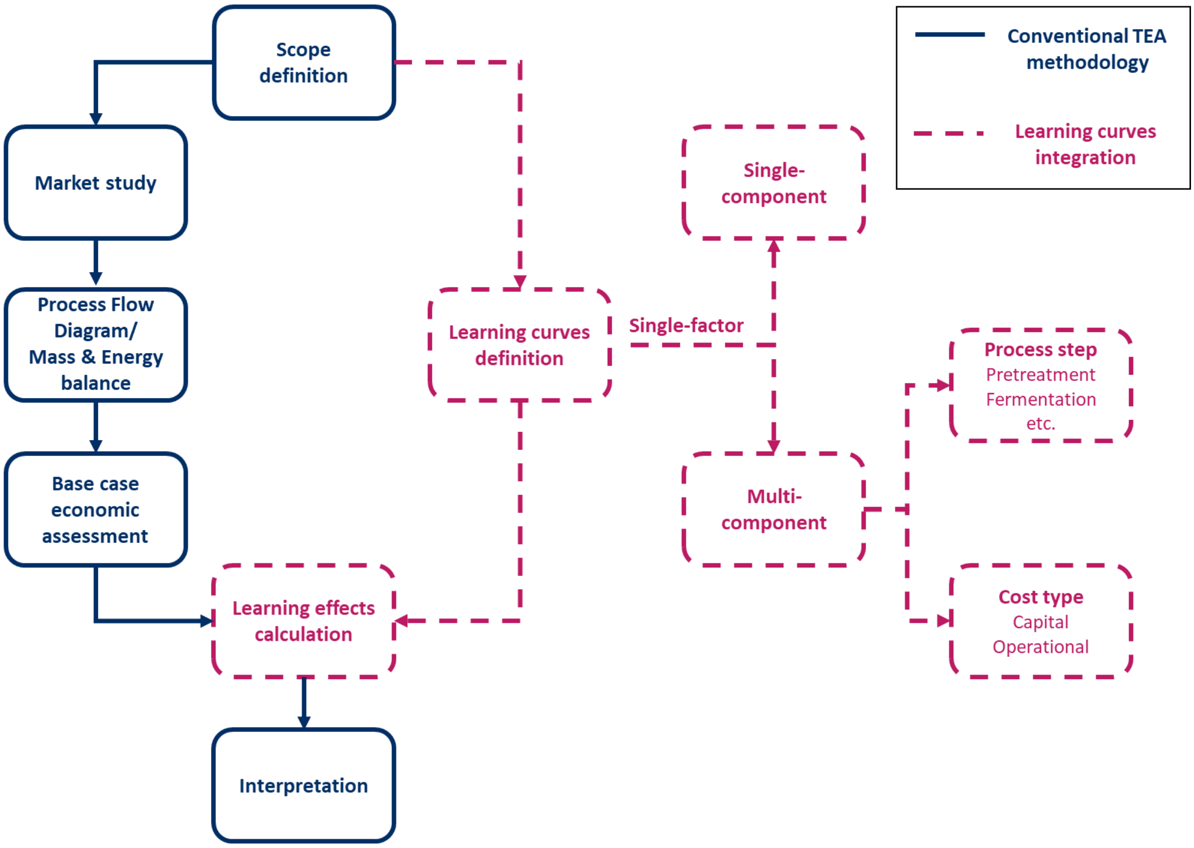

Fig. 1. Methodological TEA-learning curves framework applied in this study. Blue solid lines

represent the conventional TEA methodology and pink dashed lines the learning curves integration.

2.1 Scope definition

Firstly, the scope of the study is defined, i.e., system boundary, foreground (processes modelled) and background (fixed geographic and technological background in which the technology will be embedded).

By integrating learning curves in TEAs, it is possible to assess whether a technology can be feasible in the future due to occurring learning effects. Bioethanol production through the biochemical pathway is chosen as a technology which still exhibits high production costs, hindering its large scale commercialization. Corn stover as feedstock and bioethanol production within the Belgian territory is chosen as a case study. Corn stover supply is based on national production as well as imports, in order to investigate the effect of the biorefinery capacity to its economic performance. France and Germany are chosen as potential countries for corn stover imports, as they are among the countries with the largest corn production within the EU [29] and their proximity to Belgium facilitates the import process while limiting the costs associated to transportation. Two different scenarios for the biorefinery capacity are chosen based on the feedstock supply: (i) corn stover produced in Belgium and (ii) corn stover produced in Belgium along with corn stover imported from France and Germany.

Auxiliary areas are included in the biorefinery configuration, such as storage, utilities and energy generation, in order to reflect a real-case commercial bioethanol plant. The different maturity level of the process steps included in such a biorefinery, broadens the scope of the study further. In order to grasp this difference, a multi-component learning curve is applied as well. It should be mentioned that potential market disruptions (e.g., feedstock cost fluctuations) have been left out of the scope of this study.

2.2 Market study

Firstly, the availability of corn stover in Belgium is investigated. Corn stover is a lignocellulosic residue from corn production that can be processed as a feedstock for bioethanol production. Based on the latest available corn production data in Belgium [30] and a product yield of 1 dry kg per dry kg of corn grain [31], a total of 519 dry kt corn stover production is calculated for 2020. As one-third should remain on the field for soil quality preservation and another one-third is exploited for heat and power generation, horticulture and animal bedding [32], around 156 dry kt/year corn stover is assumed to be available in Belgium for bioethanol production.

Next, corn production in France and Germany in 2021 is investigated [33,34]. Grand Est region in France and North Rhine-Westphalia state in Germany are among the highest corn producing areas within each country, while they are neighboring with Belgium. By making the same assumptions as for Belgian corn stover, 638 dry kt corn stover in Grand Est, France and 301 dry kt corn stover in North Rhine-Westphalia, Germany are available for biofuels production (detailed data available in Table S1 of Supplementary Material).

The capacity of the biorefinery using only the Belgian corn stover as feedstock is four times lower than other TEA studies in literature [35–38] that consider large scale biorefineries, usually at a feedstock supply of 2000 dry t/day. Therefore, in order to assess the capacity impact and have a basis for comparison, import volumes are chosen in order to reach a feedstock supply of 2000 dry t/day (along with the Belgian corn stover). Given the higher biomass production in France, two-thirds of the imported quantity required is taken from France (being 364 dry kt/y) and the rest from Germany (being 182 dry kt/y). Both quantities amount up to around 60% of the available corn stover for biofuels in each area.

Corn stover price at the plant-gate includes the farm-gate cost, the required feed-handling/storage cost and the transportation cost to the plant [39]. Farm-gate prices are available for each country [40] while average transportation costs are taken within Belgium as well as from Grand Est, France and North Rhine-Westphalia, Germany to Belgium by a 40t articulated truck [41] (see Table S1 in the Supplementary Material). Feed-handling/storage data are taken the same for all countries, at 19 EUR/dry t [42]. A final corn stover price of 65 EUR/dry t originated from Belgium, 75 EUR/dry t from Grand Est, France and 119 EUR/dry t from North Rhine-Westphalia is calculated in 2021. The costs of chemicals, utilities and disposal can be found in the Supplementary Material (Table S3). Most of the prices are obtained online, while the rest from previous literature studies [38,43]. When required, costs are updated to 2021 EUR using the Producer Price Indices. Utilities include only the water supply, as electricity, steam, chilled and cooling water are produced on-site. The average bioethanol producer price is estimated at 0.726 EUR/L for 2021 in the European Union [44]. The average electricity selling price for 2021 in Flanders region of Belgium is calculated at 0.061 EUR/kWh [45].

2.3 Process model development

The conversion of corn stover to ethanol is simulated using Aspen Plus® v.12.1 [46], based on the biochemical model of Humbird et al. [38] for the National Renewable Energy Laboratory (NREL). As the biomass is supplied ready for the pretreatment process, no feed handling is required. Based on corn stover availability investigated in section 2.2, two plant capacities are investigated: (i) a smaller Plant S at 156 kt/y of dry biomass and (ii) a larger Plant L at 667 kt/y of dry biomass. The process flowsheet (**Fig. 2**) includes eight main areas: pretreatment, separate enzymatic hydrolysis & fermentation, enzyme production, product recovery, wastewater treatment, storage, energy generation and utilities. Components are selected from Aspen Component Databanks, while some are user-defined based on the NREL model . The Non Random Two Liquid (NRTL) property method is chosen as the base method for calculations, as this activity coefficient model is commonly apply when non-ideality is expected due to polar compounds, such as water and alcohols that are presented in the studied simulation models [47].

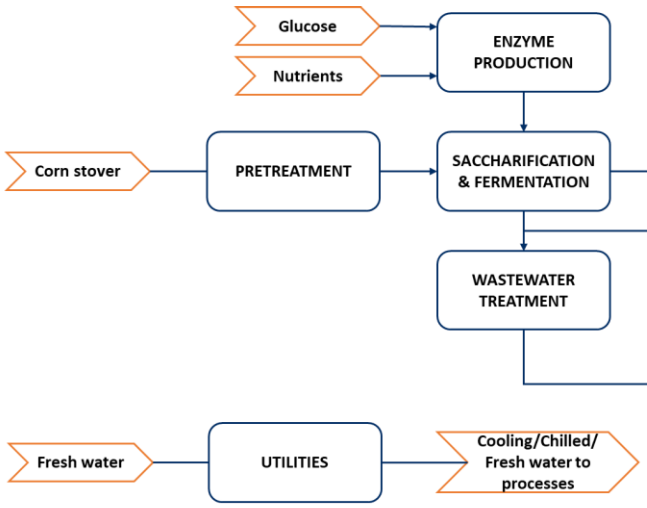

Fig. 2. Simplified process flow diagram (PFD)

The composition of corn stover can be found in the Supplementary Material (Table S2). It is assumed to be the same as the one used by Humbird et al. [38], as it provides a detailed compositional analysis that is needed for the process simulation. The moisture content is assumed to be 15 wt% (i.e., on mass basis), reflecting the average moisture content of European corn stover feedstock [48].

Four different simulation models are developed; one for each pretreatment method. Processes and operating conditions are kept the same for all models according to NREL [38], except for the pretreatment area, in order to provide a consistent basis for comparative analysis. For the two chemical pretreatment methods, sulfuric acid and sodium hydroxide are used as catalysts. Operating conditions for each pretreatment method are summarized in **Table 1**. Solids loading is set to 30 wt % for all methods, except for the liquid hot water method which is limited to 20 wt % due to the amount of water required [49].

Table 1. Pretreatment conditions for each method [38,49–52].

Conditions	Pretreatment method			
	Dilute acid	Alkaline	Steam explosion	Liquid hot water
Temperature (°C)	158	121	200	190
Residence time (min)	2	20	5	10
Severity factor	7.9	6.2	3.6	3.6
Acid/Alkali loading (mg/ dry g biomass)	22.1	20.0	-	-
Solids loading (wt %)	30	30	30	20
Conditioning	NH_3	H_2SO_4	NH_3	NH_3

After the pretreatment, a solids-liquid separation and/or water washing step is usually applied for conditioning to neutral pH and detoxification from inhibitory compounds. However, these techniques are used in laboratory-scale experiments [53]. For a large scale bioethanol plant examined in our case, conditioning with acid or base is chosen for all pretreatment methods, as a more effective technique for large volumes.

The pretreatment conversions of dilute acid pretreatment are the same as the NREL model [38]. For the rest of the pretreatment methods, assumptions are made according to lab-scale experiments with similar conditions and severity factors, in comparison to dilute acid pretreatment results [50–52]. The severity factor is calculated for all pretreatment methods according to the temperature and residence time, using equation (1). For chemical pretreatment, this factor is adjusted in order to take into account the acid or alkali loading, using equation (2) [54].

$$SF = \log\left(t \cdot \exp\left(\frac{T - 100}{14.75}\right)\right) \quad (1)$$

$$SF = \log\left(t \cdot \exp\left(\frac{T - 100}{14.75}\right)\right) + |pH - 7| \quad (2)$$

Where, SF denotes the severity factor, t the residence time (min), T the pretreatment temperature (^{o}C) and pH the pH of the pretreated slurry. The fractional conversions chosen for the four different pretreatment methods can be found in the Supplementary Material (Table S4).

2.4 Process economics

An economic assessment for each biorefinery with a different pretreatment method and capacity is applied to evaluate the economic feasibility of ethanol production from corn stover in Belgium. All values used in the analysis are in 2021 euros (EUR 2021). The main economic assumptions of the model are presented in **Table 2**. A discounted cash flow analysis is conducted for all models and the minimum fuel selling prices (MFSP) are calculated.

Table 2. Techno-economic assessment parameters.

Parameter	Value	Source
Plant lifetime (years)	20	Assumption
Year of analysis	2021	Assumption
Discount rate (%)	15	[28]
Tax rate (%)	25	[55]
Depreciation period (years)	General plant: 7 Energy generation plant: 20	[56]
Depreciation method	Linear	Assumption
Annual operating hours (h)	8000	Assumption
Working capital (EUR)	5% of FCI	[38]
Land cost (EUR)	2% of FCI	[57]

2.4.1. Capital Expenditure (CAPEX)

Purchasing cost of equipment is obtained from the NREL report for all areas [38], as it is based on vendor equations for specialized equipment. For the different pretreatment areas, the cost of relevant process equipment (such as pumps, heat exchangers) is based on data from the NREL [38], while the pretreatment reactor costs are adjusted according to literature [58]. Costs are scaled for each equipment type using NRELs' values as the base case [38] and mass and energy balances obtained from the ASPEN Plus process model as the new case, based on the following equation:

$$New\ cost = (Base\ cost) \cdot (\frac{New\ size}{Base\ size})^k \quad (3)$$

Where, k is the scaling exponent, ranging from 0.5 to 0.8, depending on the equipment type used [38]. The Chemical Engineering Plant Cost Indices are applied to adjust the cost to the analysis year of 2021 while NRELs' installation factors for each equipment type are used to calculate the final equipment cost [38].

The Fixed Capital Investment (FCI) is calculated as the sum of the Total Direct Cost (TDC) and Total Indirect Cost (TIC), according to **Table 3**. Finally, the CAPEX of the biorefinery is estimated for each pretreatment method by summing up the FCI, working capital and land cost.

Table 3. Total Direct and Indirect Cost assumptions [38]. ISBL: Inside Battery Limits

Parameter	Value

Total Direct Cost (TDC)	
Warehouse	4% of ISBL
Site development	9% of ISBL
Additional piping	4.5% of ISBL
Total Indirect Cost (TIC)	
Prorateable expenses	10% of TDC
Field expenses	10% of TDC
Home-office & construction fees	20% of TDC
Project contigency	10% of TDC
Other costs	10% of TDC

2.4.2 Operational Expenditure (OPEX)

The annual operating cost is calculated as the sum of the variable and fixed operating costs. The variable operating cost is estimated based on the mass and energy balances of the process simulation and the costs of feedstock, chemicals, utilities and disposal.

Monthly wages for operators in chemical industries in Belgium were estimated at 3534 EUR in 2019 [59]. Based on Sinnott and Towler's operator shift positions analysis [43], a 102 EUR/h total operating labor cost is estimated. The final operating cost also includes the supervision, direct salary overhead, maintenance and property taxes and insurance, which are calculated as described in **Table 4**.

Table 4. Fixed operating cost assumptions.

Parameter	Value	Source
Supervision	25% of operating labor	[43]
Direct salary overhead	50% of operating labor and supervision	[43]
Maintenance	0.5% of CAPEX	[60]
Property taxes and insurance	0.7% of FCI	[38]

Finally, a break-even point analysis is carried out in order to calculate the cost reduction needed to reach a profitable investment. The analysis is executed twice for each simulation model, by considering cost as CAPEX and as ethanol production cost. For this analysis, the ethanol price in 2021 along with projections up to 2030, is taken from the OECD-FAO Agricultural Outlook 2022 [44]. The ethanol production cost C_{EtOH} (EUR/L) is calculated using Equation (4):

$$C_{EtOH} = \frac{CAPEX \cdot r + OPEX}{Q_{EtOH}} \tag{4}$$

Where r is the annuity factor and Q_{EtOH} is the annual ethanol production (L/y). The annuity factor is calculated based on the discount rate and plant lifetime [61].

2.5 Learning curves definition

Different mechanisms exist for the learning process, sometimes overlapping each other. The most studied mechanism is learning-by-doing, which is caused by the repetition of the production process of the technology. Other learning effects that have been identified are learning-by-using, which occurs when the technology reaches the market and user experience feedback is received, learning-by-searching, which arises from R&D investments and finally learning-by-interacting, which originates from knowledge diffusion [14]. The effect of these different learning mechanisms can be assessed through the multi-factor learning curve. A two-factor learning curve has been suggested by Kouvaritakis et al. [62], which takes into consideration both learning-by-doing and learning-by-searching effects. However, the single-factor learning curve is the most commonly used one in the energy sector, as it considers several learning mechanisms into one factor and requires less data [63]. The learning curves studied in this article are all single factor, hence we decided to not explicitly mention "single factor" in the remainder of this work. Two different learning curves, based on the component-learning approach, are studied in this article [64].

2.5.1 Single-component learning curve

The single-component learning curve considers only one component, the unit cost of production, and is expressed as [17]:

$$C = C_0(\frac{P}{P_0})^{-a} \tag{4}$$

Where P is the cumulative production, C is the unit cost of production at P, C_0 and P_0 are the unit cost and cumulative production at an arbitrary starting point and a is the learning coefficient.

The corresponding learning rate (LR) expresses the cost reduction per doubling of cumulative production and is calculated as [17]:

$$LR = 1 - 2^{-a} \tag{5}$$

2.5.2 Multi-component learning curve

The single-component learning curve can be extended to the multi-component learning curve, which expresses the cost as a sum of its individual components with potentially different learning rates (and hence learning coefficients a_i) [64]:

$$C = \sum_{i=1}^{n} C_0^i \, (\frac{P^i}{P_0^i})^{-a_i} = C_0^1 \, (\frac{P^1}{P_0^1})^{-a_1} + C_0^2 \, (\frac{P^2}{P_0^2})^{-a_2} + \cdots + C_0^n \, (\frac{P^n}{P_0^n})^{-a_n} \tag{6}$$

Where n is the number of components. This approach allows for a better estimation of learning effects on new technologies, as each individual component has a different learning rate.

The choice of components can vary based on the desired outcome of the study. Many definitions of components exist in literature, but no structured framework including different possibilities is mentioned. The first step is to separate the overall technology into different production pathways. For example, Upstill & Hall [65] have considered the onshore/offshore depleted oil and gas fields and onshore/offshore deep saline aquifers as different technology variants of carbon dioxide storage. Then, they applied the multi-component learning curve for each of these variants. Once this is done, the technology variant can be split into different components. One option is to disaggregate the technology into multiple process steps. Karka et al. [21] have divided methanol production into two main process steps: gasification and synthesis. These main processes were further subdivided and learning rates were estimated based on the maturity of each step. Finally, considering the overall cost as a sum of different cost types, such as equipment and operational costs, is another alternative when applying the multi-component learning curve [17,65].

These approaches can be applied to the case of advanced biofuels production. This study focuses only on the biochemical production pathway of advanced biofuels, thus different process steps and cost types are considered as components for this technology variant. The biochemical production route is a complex pathway that requires multiple process steps such as pretreatment, enzymatic hydrolysis and fermentation. The overall production cost of biofuels can be split into the capital and operational expenditure.

Due to the challenge in calculating the learning effects for different components, an optimization-based approach is suggested. Multivariable optimization methods can be applied to calculate the minimum learning rates needed in order to reach an economically feasible technology level.

2.6 Learning effects calculation

Two biorefinery capacities and four biorefinery configurations, with different pretreatment technologies are assessed with two single-factor learning curves: the single- and multi-component. On the single-component learning curve, two different scenarios are created by assuming a cost reduction on CAPEX and on the ethanol production cost. The multi-component learning curve is applied for two different types of components: cost types and process steps. The first is a two-component and the latter an eight-component learning curve, which are both solved for two different scenarios.

The starting point of the learning curves is considered to be 2021, the year of analysis of the base case economic assessment performed previously. The cumulative production is assumed to be the total cellulosic ethanol produced in the EU during 2021, being 50 million L (ML) [12], and based on projections by 2030 (see Figure S4 of Supplementary Material), this will be 10 billion L (BL) [66]. The initial costs are estimated from the base case economic assessment, while the costs in 2030 are estimated based on the cost reduction break-even point analysis. The learning coefficients are calculated as mentioned below for each learning curve model:

2.6.1 Single-component learning curve

The single-component learning curve is applied for the four different simulation models and for two scenarios: considering a cost reduction in the CAPEX and in the ethanol production cost. The learning coefficients are calculated from Equation (4) and the learning rates from Equation (5).

2.6.2 Multi-component learning curve

The optimization problem is formulated as the minimization of an objective function expressing the square of the difference between the cost required to reach economic feasibility (C^*, result of the break-even point analysis of the TEA) and the learning curve (which has an absolute minimum of 0), subject to bound constraints on the learning coefficients. The learning coefficients are the optimization variables which can be translated to learning rates using Equation (5).

The optimization problem is expressed as:

$$\min_{a} f^2(a) = \min_{a}(C^* - \sum_{i=1}^{n} C_0^i \left(\frac{P^i}{P_0^i}\right)^{-a_i})^2 \tag{7}$$

$$s.t.$$

$$A \cdot a \leq b$$

$$a^L \leq a \leq a^U$$

Where a, b, a^L and a^U are vectors (with $a \in \mathbb{R}^n: a \geq 0$) and A is a matrix. A MATLAB non-linear programming function, *fmincon*, is applied, using the default Interior Point Method (IPM), with tolerance taken as 10^{-6} and maximum iterations as 1000.

In this article it is assumed that a maximum feasible value for the learning rate is around 50%, as learning rates of up to 43.7% are mentioned in literature based on rules-of-thumb approaches [17]. Different initial values a_0 and upper bound constraints a^U are tested, in order to get different minima in the specified range, which could provide more realistic results. Two different optimization problems are formed by considering components as (a) cost types and as (b) process steps.

2.6.2.1 Components: cost types

The ethanol production cost consists of the discounted capital and the operational cost. Therefore, a two-component curve is formed:

$$f(a) = C - \sum_{i=1}^{2} C_0^i \left(\frac{P^i}{P_0^i}\right)^{-a_i} = C - C_0^1 \left(\frac{P^1}{P_0^1}\right)^{-a_1} - C_0^2 \left(\frac{P^2}{P_0^2}\right)^{-a_2} \tag{8}$$

where i=1 refers to the discounted CAPEX and i=2 refers to the OPEX.

There are two possible constraints for the a_1 and a_2: $a_1 \leq a_2$ and $a_1 \geq a_2$.

2.6.2.2 Components: process steps

The ethanol production cost can be split into the production costs of each process area of the biorefinery. Therefore, an eight-component ($n = 8$) curve is formed:

$$f(a) = C - \sum_{i=1}^{8} C_0^i \left(\frac{P^i}{P_0^i}\right)^{-a_i} = C - C_0^1 \left(\frac{P^1}{P_0^1}\right)^{-a_1} - \cdots - C_0^8 \left(\frac{P^8}{P_0^8}\right)^{-a_8} \quad (9)$$

where i=1 is the pretreatment, i=2 the enzymatic hydrolysis & fermentation, i=3 the enzyme production, i=4 the product recovery, i=5 the wastewater treatment, i=6 the storage, i=7 the energy generation and i=8 the utilities area.

Each process step has different products. However, it can be assumed that: $P^i/P_0^i = P^4/P_0^4 = \text{const}, \ \forall i \in \{1, \ldots, n\}$, where P^4 and P_0^4 are the main output of the product recovery area, meaning the cumulative cellulosic ethanol production in EU by 2030 and 2021 respectively.

Due to the eight-component learning curve, there are many possible constraint combinations. Two different scenarios are formed based on the maturity of each component. In the first scenario (scenario A), all auxiliary process areas (i=5,6,7,8) are assumed mature and no learning is expected. For the rest, pretreatment is assumed to be the least mature process followed by enzymatic hydrolysis & fermentation, enzyme production and product recovery areas. In the second scenario (scenario B), storage and utilities areas are assumed to have a zero learning rate. Wastewater treatment and energy generation areas are also expected to have a learning rate less than 1% (resulting in an upper bound of 0.0145 for the learning coefficients a_5, a_7). For the rest, pretreatment is assumed to be the least mature process followed by enzymatic hydrolysis & fermentation, enzyme production and finally product recovery areas [67,68].

To sum up, two learning curves, the single- and multi-component, are applied for a biorefinery with two different capacities (Plant S and Plant L). Each biorefinery is investigated for four different configurations based on the pretreatment method applied (dilute acid, alkaline, steam explosion and liquid hot water). Each learning curve is applied for two different scenarios: the single-component curve for a cost reduction in (i) the CAPEX and in (ii) the ethanol production cost and the multi-component curve by taking components as (i) cost types and (ii) process steps. In order to solve the curves, two different scenarios are also applied during the optimization-based calculations for the constraints.

3. RESULTS AND DISCUSSION

3.1 Process simulation results

The main process results, including inputs and outputs, are presented in **Table 5**. The ethanol yield (considering corn stover's LHV as 17.4 MJ/kg [48] and bioethanol's LHV as 26.7 MJ/kg [36]) was calculated at 0.40 MJ of ethanol per MJ of biomass for the dilute acid model, 0.26 MJ/MJ for the alkaline model, 0.35 MJ/MJ for the steam explosion model and 0.34 MJ/MJ for the liquid hot water model. This can be explained by the fact that the dilute acid pretreatment is well studied through the years in literature and the simulation model developed by NREL is optimized for theoretical yields [38].

Table 5. Major process simulation and economic assessment results for each simulation model.

Values	Plant S				Plant L			
	Dilute acid	Alkaline	Steam explosion	Liquid hot water	Dilute acid	Alkaline	Steam explosion	Liquid hot water
Process Inputs								
Corn stover (dry t/day)	468	468	468	468	2000	2000	2000	2000
Chemicals (t/h)	2.50	2.30	1.40	1.40	11.0	10.0	6.00	6.20
Fresh water (t/h)	35.2	47.5	39.7	41.5	153	201	168	180
Process Outputs								
Ethanol (L/min)	108	70.2	94.4	90.3	463	300	404	386
Excess electricity (MW)	2.00	7.10	2.70	2.10	13.0	39.0	16.0	13.0
Base case economic results								
CAPEX (M EUR)	177	180	170	175	439	444	421	435
OPEX (M EUR/year)	22.0	20.6	19.6	19.7	92.1	85.8	81.6	82.3
MFSP (EUR/L)	1.04	1.50	1.10	1.18	0.75	1.04	0.79	0.85
Break-even point analysis results								
CAPEX (M EUR)	50.8	19.5	45.0	37.9	225	98.1	198	168
Ethanol production cost (EUR/L)	0.499	0.558	0.503	0.498	0.538	0.613	0.541	0.535

The highest chemical consumption is evidently observed for the chemical pretreatment methods, in contrast to the physicochemical methods. Indeed, the pretreatment area accounted for around 26-28% of chemicals use for the dilute acid and alkaline models, while the physicochemical pretreatment methods accounted for around 7% (conditioning included), verified in both of the investigated plant capacities.

Water requirement was calculated at 68 t water per L EtOH for the dilute acid model, 103 t/L for the alkaline model, 79 t/L for the steam explosion model and 89 t/L for the liquid hot water model. This includes both fresh and recycled water. The high water demand for the alkaline pretreatment model is mainly attributed to the increased need for cooling water for the energy generation area, due to the large amount of lignin removed during this pretreatment, which is used as a combustible stream. The water requirement for the pretreatment reactor and the low solids loading are responsible for the high water consumption of the liquid hot water model.

The electricity demand on-site was found to be similar for all models, around 1.4 GJ/dry t biomass. However, the electricity available as a by-product was found to be the highest for the alkaline model, due to the high delignification rate of this pretreatment method. On the other hand, steam demand was calculated at 19 GJ/dry t biomass for the steam explosion model and 22 GJ/dry t biomass for the liquid hot water model. The largest amount of steam is used for preheating the biomass stream at the pretreatment temperature as well as maintaining the reactor temperature. The rest of the steam is mainly used by the distillation process in the product recovery area. Indeed, the steam demand for the physicochemical pretreatment methods is almost two times higher than the alkaline model, which had the lowest pretreatment temperature as well as ethanol production.

3.2 Economic assessment results

The main economic indicators for each biorefinery configuration are summarized in **Table 5**. All values are in 2021 EUR.

The alkaline pretreatment model exhibits an overall higher CAPEX than all models, which can be attributed to the bigger equipment required for the energy generation area, due to the high lignin removal of this pretreatment method, which is used as a fuel stream for steam and electricity production. Notably, the energy generation and wastewater treatment areas account for more than half of the calculated equipment cost, around 33% and 22% respectively. The lowest OPEX is observed for steam explosion and liquid hot water due to the lack of chemicals use. However, the difference on the OPEX between the pretreatment models is not significant (ranging from 5 to 10%). This is attributed to the fact that feedstock supply has the highest contribution to the annual operating cost, around 50%, with chemicals following at around 30%. This is the case for Plant S. However, feedstock contribution is even higher for Plant L, around 60-65%, due to the higher corn stover price of the imported quantities.

The ethanol production costs were estimated to be the lowest for the dilute acid model (0.96 EUR/L), followed by steam explosion (1.02 EUR/L), liquid hot water (1.09 EUR/L) and alkaline pretreatment (1.44 EUR/L) for Plant S. Despite the high operating cost estimated for the dilute acid pretreatment method, the ethanol production cost for this model was the lowest due to its high ethanol yield. Similar observations are made for the Plant L, but the production costs are around 24% lower than Plant S for all models.

For both of the investigated plant capacities, the dilute acid pretreatment model has the lowest MFSP, followed by steam explosion and liquid hot water. The calculated MFSPs for the Plant L are approximately 30% lower for all models. The lowest obtained MFSP is for the dilute acid model of Plant L, at 0.75 EUR/L. Similar results were obtained by Silva et al. [22], who observed a better economic performance for the dilute acid pretreatment compared to steam explosion and liquid hot water, despite these having a lower capital cost. A lower MFSP is also calculated by Tao et al. [18] for the dilute acid model, compared to the thermochemical and alkaline pretreatments.

Fig. 3 shows the breakdown of MFSP for the different pretreatment models and the two plant capacities investigated in this study. The return on investment and feedstock supply are the two parameters with the highest contribution for all models studied, over 50% (combined) of the MFSP for both plant capacities. Capital depreciation, cost of chemicals and income tax showed a big impact on the MFSP as well. By-product credit contribution was significantly higher for the alkaline pretreatment model than the rest of the models, due to the higher excess electricity production. As indicated earlier, feedstock cost has a bigger contribution to the MFSP for Plant L, 30% instead of 20% on average, due to the imported corn stover amount.

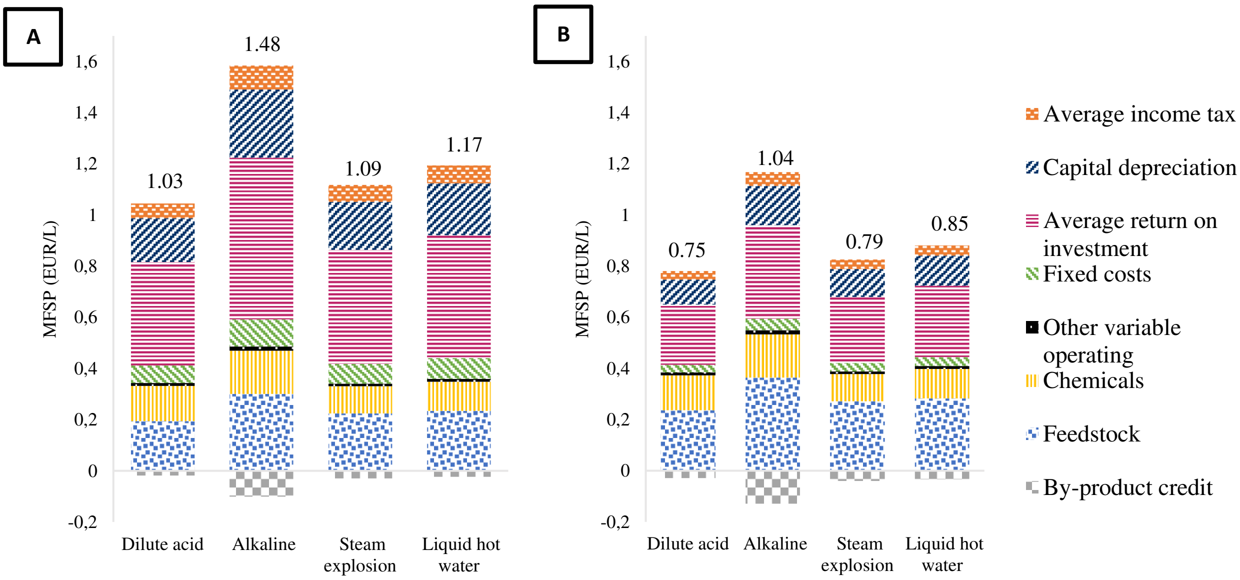

Fig. 3. Minimum fuel selling price breakdown for four different pretreatment models for Plant S (A) and Plant L (B). Values above stacks indicate the final MFSP by taking into account the by-product credit.

The costs calculated from the break-even point analysis are presented in **Table 5**. As far as the CAPEX is concerned, there is a need for 71% reduction by 2030 for the dilute acid model, 89% for the alkaline model, 74% for the steam explosion model and 78% for the liquid hot water model to reach a profitable investment for Plant S. A 50-78% cost reduction was also calculated for the different pretreatment models of Plant L. Such cost reductions are high and have a small potential to occur in reality. However, when the total production cost is considered, the cost reductions are estimated at 48, 61, 51 and 54% for each model respectively of Plant S, while even smaller cost reductions are calculated for Plant L. These results indicate that a reduction solely in the CAPEX is not enough and other costs, such as the operating costs need to be reduced. The potential of achieving such cost reductions by 2030 through technology learning is investigated in the following subsection 3.3.

3.3 Single-component learning curve

The learning rates are calculated based on the single component learning curve for two different cases: assuming a cost reduction in CAPEX and in the ethanol production cost, as shown in **Fig. 4**. The cost at the end of the learning curve corresponds to the cost required to reach a profitable investment by 2030.

Considering a cost reduction only in the capital investment, the learning rate is found the lowest for the dilute acid model at 15.1% for Plant S and at 8.4% for Plant L. Steam explosion and liquid hot water models follow, while the alkaline model requires almost a 1.5 to 2 times higher rate than the dilute acid model due to its high CAPEX. However, when the total production cost is taken into consideration, the results are more similar for all models, with an average learning rate of about 9.4% for Plant S and 5.3% for Plant L, while the dilute acid model exhibited the lowest learning rate, at 8.2% and 3.9% for Plant S and Plant L respectively.

The learning rates calculated for both cases are in accordance with the economic performance of each process model, as discussed previously. Namely, dilute acid and steam explosion models showed the best economic performance, thus a lower learning rate is required in comparison to the rest of the models investigated in this study. Also, the higher plant capacity of Plant L showed an overall better performance, thus the learning rates obtained for this plant are significantly lower, around 30-50%, than Plant S.

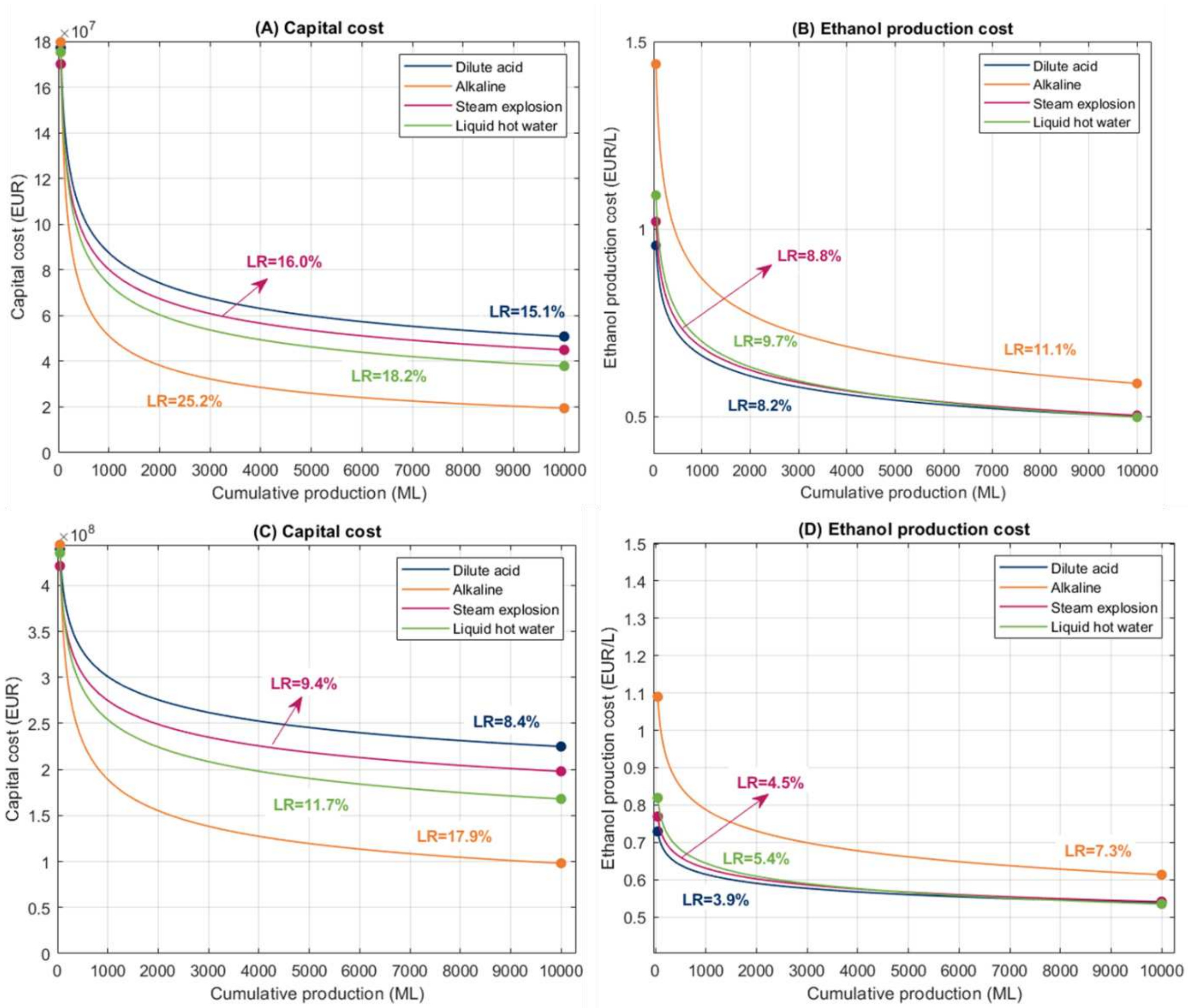

Fig. 4. Single-component learning curve for Capital cost reduction (A) and Ethanol production cost reduction (B) in Plant S and Capital cost reduction (C) and Ethanol production cost reduction (D) in Plant L. The learning curve is blue for the dilute acid model, orange for the alkaline model, magenta for the steam explosion model and green for the liquid hot water model. The learning rates obtained for each model are also displayed. The points indicate the starting point, 2021 (left), and the ending point, 2030 (right), of the analysis.

3.4 Multi-component learning curve

3.4.1 Components: cost types

The results for the multi-component learning curve, by considering components as cost types, are summarized in **Fig. 5** for Plant L (results for Plant S can be found in Figure S5 of Supplementary Material). The lowest learning rates for both components and constraint cases are obtained for the dilute acid model, followed by steam explosion, liquid hot water and alkaline models. This observation agrees with the economic performance of each model as discussed before. In general, learning rates are around 30-60% lower for Plant L than Plant S, indicating its higher potential for reaching economic feasibility by 2030.

By lowering the upper bound constraint, more feasible solutions are obtained, as the difference between the learning rates of the two components diminishes. For example, a combination of learning rates at 18% for CAPEX and 2% for OPEX is less probable to occur than a 13% and 4% respectively for the alkaline model of Plant L. Therefore, different upper bounds are included in the presented results, as alternative scenarios, for which the optimization objective and constraints were satisfied.

For the first constraint case, where a higher learning rate is expected for the operational cost than the capital cost reduction, the learning rates are within the range of 1.6 – 3.3% for CAPEX and 6.0 – 13% for OPEX. The learning rate for the first component is 3 to 5 times lower than the second component. A similar observation is also made when a higher learning rate is chosen for CAPEX than OPEX, as learning rates for the first component range within 7.7 – 18% and 1.5 – 3.9% for the second.

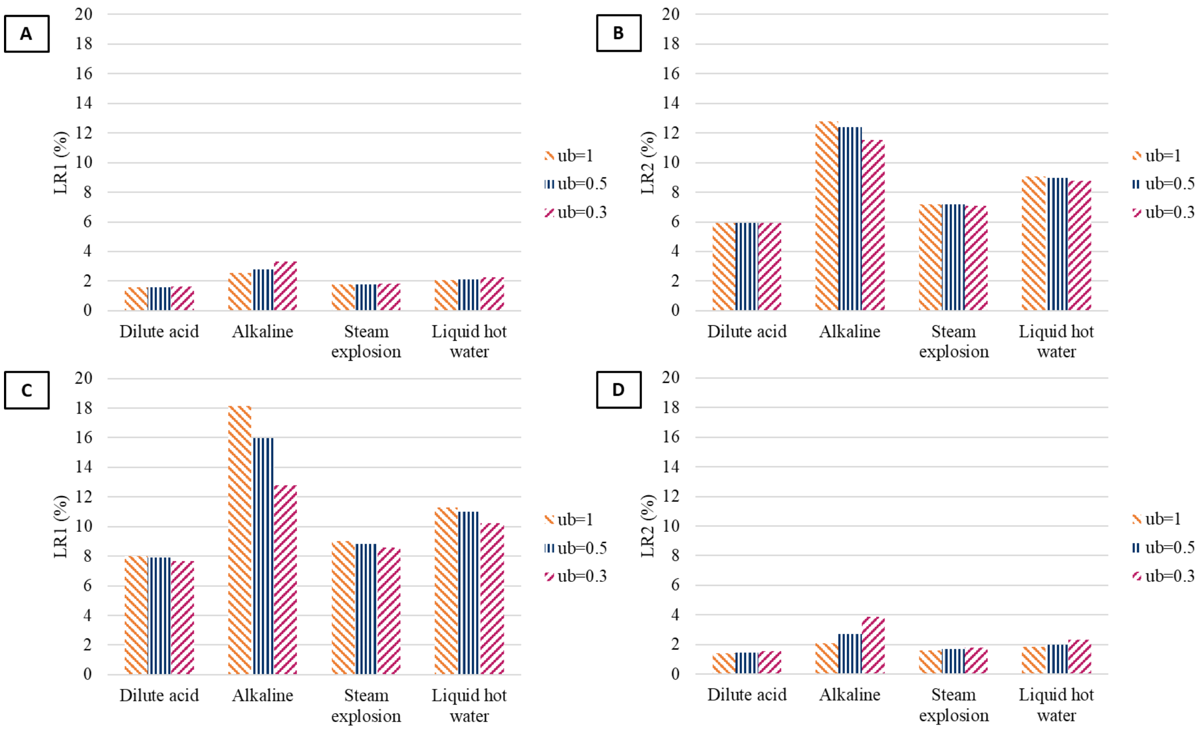

Fig. 5. Multi-component learning rates of Plant L for CAPEX (A) and OPEX (B) for $\alpha_1 \leq \alpha_2$ and CAPEX (C) and OPEX (D) for $\alpha_1 \geq \alpha_2$. α_1: learning coefficient for CAPEX, α_2: learning coefficient for OPEX, LR: learning rate, ub: upper bound

3.4.2 Components: process steps

The results for the multi-component learning curve, considering process steps as components, are presented in **Fig. 6** for scenario A of Plant L (results for Plant S available in Figure S6 of Supplementary Material). In scenario A, all auxiliary areas are assumed to have a zero learning rate, thus only four learning rates are calculated. The learning rates calculated for the pretreatment area of the dilute acid pretreatment are around 1.3, 2 and 5 times higher than for the enzymatic hydrolysis & fermentation, enzyme production and product recovery areas, respectively. These differences become smaller when the upper bound constraint is set at 0.5. Similar observations are also made for the physicochemical pretreatment methods, while the alkaline model requires almost equally high learning rates for all its areas.

Results for the scenario B of Plant L are presented in **Fig. 7** (results for Plant S available in Figure S7 of Supplementary Material). The learning rates here are slightly smaller than scenario A, as more process areas are assumed to contribute to the total cost reduction. However, the wastewater treatment (i=5) and energy generation (i=7) areas, which are now included in the learning curve, are assumed to have a small learning rate and therefore a small impact on the cost reduction. Therefore, no significant differences are observed between the two scenarios. Among all models and for both scenarios, the highest learning rates are calculated for the pretreatment area (i=1) of the alkaline model, which indeed presented the worse economic performance.

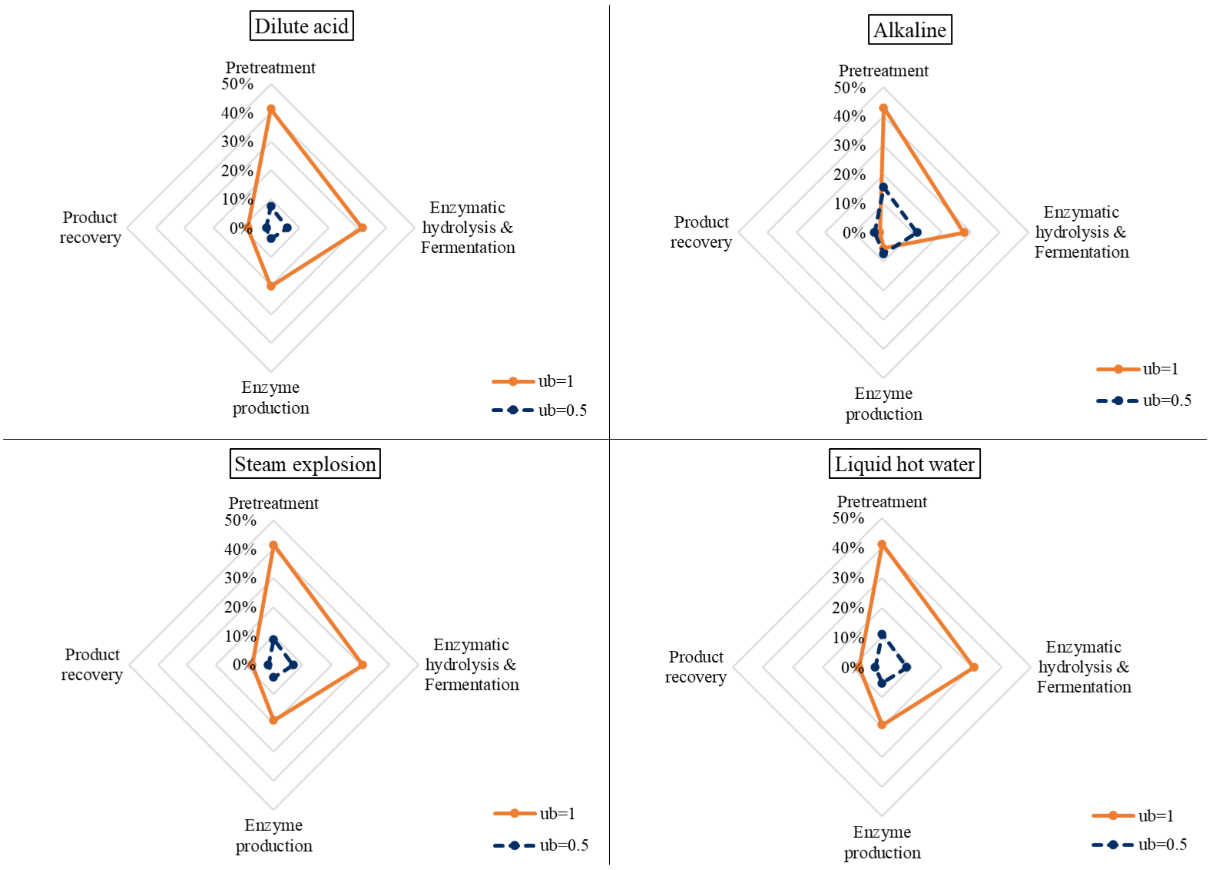

Fig. 6. Multi-component learning rates of Plant L obtained for the four different process models by considering components as process areas for scenario A: only four process steps are included as the rest of the areas are assumed have a learning rate of zero. Results are presented for two different upper bounds (ub).

Overall, higher learning rates were calculated for Plant S compared to Plant L for both scenarios. Especially for the lower upper bound (ub=0.5), learning rates of 2 to 3 times lower were calculated for Plant L for both scenarios.

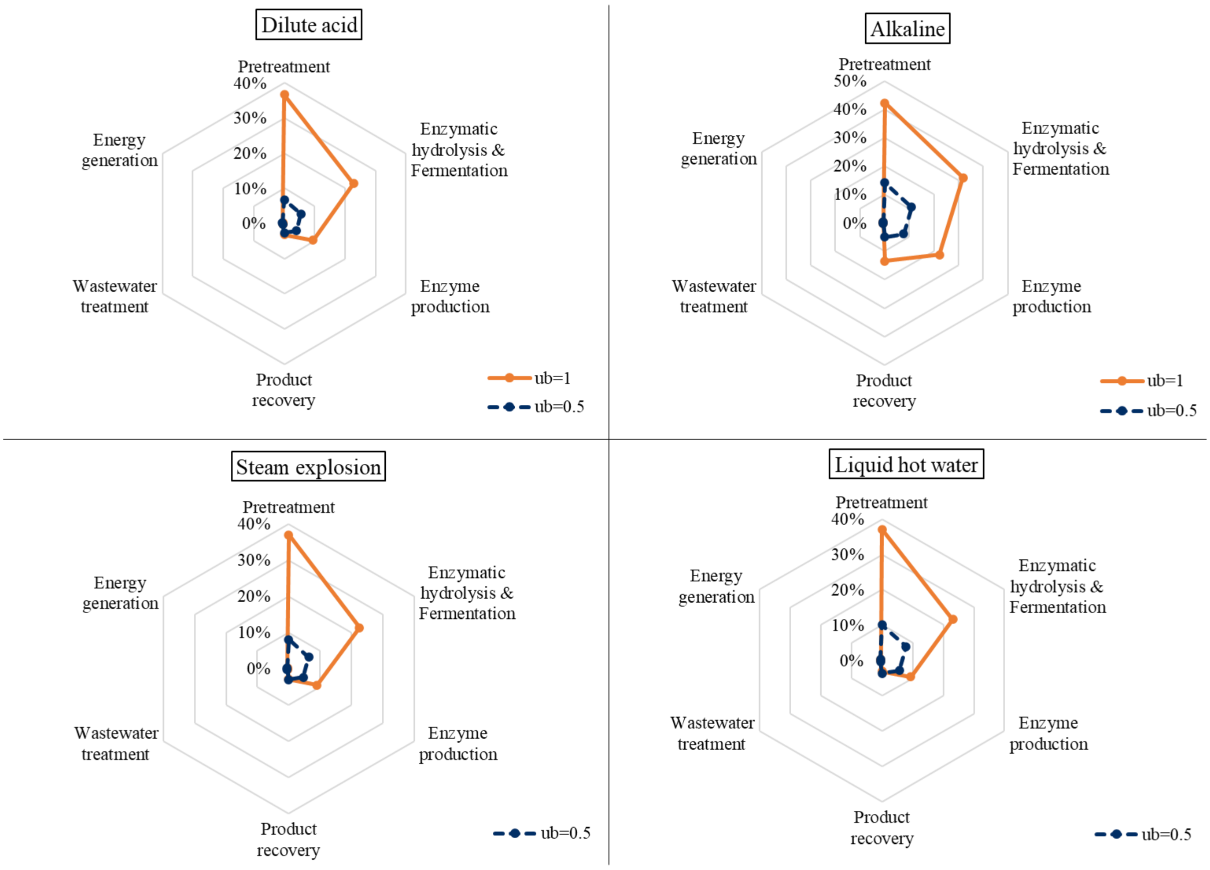

Fig. 7. Multi-component learning rates of Plant L obtained for the four different process models by considering components as process areas for scenario B: six process areas are included as storage and utilities areas are assumed to have a learning rate of zero. Results are presented for two different upper bounds (ub).

3.5 Discussion

The economic assessment performed in this study can be used to assess the potential of second-generation ethanol production from corn stover in Belgium. Because of the importance of the scale, two different plant capacities were investigated. Indeed, the larger plant capacity of Plant L, showed an overall improved economic performance.

Firstly, an important remark is that the equipment cost in this study is based on actual vendor/manufacturer prices, taken from Humbird et al. [38]. This report dates back to more than a decade ago and despite the use of CEPCI for updating the costs to the year of analysis, there is an uncertainty around the accuracy of these costs. Thus, it is important to assess the impact of the CAPEX on the economic performance of the investigated bioethanol plant. This can be addressed by performing a Monte Carlo simulation, taking a triangular distribution for the capital cost based on a 20% variance (applied for the dilute acid model of Plant S as a case study). The 20% variance is chosen based on capital costs estimations in ASPEN Plus Capital Cost Estimator software, where equipment costs in 2021 values were obtained, estimating a 20% decrease in CAPEX compared to the base case calculations. The calculated MFSP ranges from 0.91 to 1.15 EUR/L, meaning that an up to 11% decrease in the MFSP can occur in case of a decreased capital cost (detailed results available in Figure S8 of Supplementary Material). Indeed, the capital cost has a significant impact in the economic performance of the biorefinery, however, estimating the cost of equipment is a challenging task for specialized units, which are not usually available in capital cost estimator packages.

More than 50% of the calculated capital cost was attributed to the energy generation and wastewater treatment areas. Steam and electricity are produced on-site, at the energy generation area, thus raising the question of whether this is the optimal option. An alternative scenario could be that of excluding the energy generation area, buying electricity, HP steam and LP steam from suppliers, while selling lignin and biogas produced in the wastewater treatment area as by-products to the market for further processing (prices available in Table S3 of Supplementary Material). Performing such a scenario for the dilute acid model indicated a 2% decrease in the MFSP for Plant S and a 5% increase for Plant L (see Table S5 of Supplementary Material). However, there is a lot of uncertainty surrounding the pricing of lignin and biogas as by-products (e.g. lignin prices can reach up to 330$/t [69]), which can have a big impact on the economic viability of the plant. Also, in case of taking the environmental impact into consideration, the energy produced on-site is accounted as renewable energy (deriving from biomass), while the utilities supplied by the market could rely on fossil-based energy. Thus, based on these preliminary results the inclusion of energy produced on-site is deemed as a better solution for large-scale capacities, while more research needs to be conducted for smaller scale biorefineries, in order to identify the optimal strategy.

As far as the wastewater treatment area is concerned, the major source of wastewater in biorefineries is the stillage which has a high chemical oxygen demand (COD) content, low pH and dark brown color (mainly caused by melanoidins) [70]. Wastewater composition varies depending on the feedstock type and processes used [71]. For lignocellulosic biorefineries, the various chemicals added (e.g. ammonia) or produced (e.g. furans) during the pretreatment process have a high impact on the wastewater composition [72].

In this study, the operating conditions and specialized equipment required are modelled according to Humbird et al. [38], assuming a 99.6% total COD digestion. The wastewater treatment area is treating the condensed pretreatment vapor as well as the filtered stillage and boiler and cooling tower blowdown streams. A combination of anaerobic digestion producing biogas (51% CH_4 and 49% CO_2 on a dry molar basis) and aerobic digestion producing treated water and sludge is applied. Membrane filtration is used to remove the total suspended solids and reverse osmosis to remove the dissolved inorganic salts. The anaerobic digestion is modelled to digest 91% of each organic component and the aerobic digestion to further digest 96% of the remaining COD. Sulfates produced during the detoxification step of pretreatment are converted to hydrogen sulfide in the biogas (removed later at the energy generation area) while a nitrification step is applied to remove the present ammonium ions. However, due to the high organic rates, the suggested wastewater treatment processes pose challenges. In particular, achieving the anaerobic COD removal rate simulated in this study might be hard and quite optimistic. In literature, COD removals of up to 79% in a CSTR anaerobic reactor [73] and up to 89% in a fluidized bed reactor [74] have been obtained in pilot-scale experiments for wastewater from corn-stover bioethanol plants.

Given the Importance of wastewater treatment and upstream processes in the overall economic performance of a biorefinery [72], small changes in the slurry composition can vary significantly the costs associated with this area. This is also verified by our results, as the alkaline pretreatment model requires a 5-9% less expensive wastewater treatment area, due to the limited amount of side-compounds produced during the pretreatment. It is also worth mentioning that, except for the economic impact, the wastewater treatment can affect significantly the environmental performance of the biorefinery [71]. Indeed, biorefinery effluents are toxic, having a direct impact in soil and water contamination, human toxicity and water eutrophication, while the presence of significant amounts of side-compounds can lower the biodegradability (i.e. biodegradable COD) of the wastewater [70,71]. Nowadays, much research is conducted in developing novel methodologies that can improve both the economic and environmental performance, while achieving higher than 95% COD removal [71].

The calculated MFSPs were benchmarked with the current average bioethanol price in the market, indicating that for large capacities, second-generation bioethanol can be competitive with the conventional bioethanol. An even better economic performance could be achieved by optimizing the feedstock supply chains, in terms of importing quantities, exporting countries and transportation modules, however this is left out of the scope of this study.

On the other hand, for small-scale biorefineries, the potential is quite limited at the moment. Higher process efficiencies and yields could potentially increase the ethanol production, and thus the annual revenues from ethanol sales. More research in the field of different pretreatment methods for lignocellulosic biomass could achieve this target. The relatively worst results obtained for the alkaline pretreatment do not mean that this pretreatment method should be neglected. The high delignification rate of this method could be exploited in different ways, instead of using lignin solely as a fuel stream for steam and electricity production. Much interest is given lately to lignin valorization through the production of high-value chemicals and materials, known as lignin-first biorefineries [75,76]. These by-products could offer extra biorefinery revenues and thus improve its economic viability.

It should be pointed out that benchmarking advanced biofuels with conventional biofuels is a practice applied by multiple recent studies in the field [77–79], due to the limited amount of data on advanced biofuels markets. Given the continuously increasing share of advanced biofuels by 2030 as well as the increased blend-in mandates in EU countries [80], a separate market for advanced biofuels is likely to be created in the near future. The International Renewable Energy Agency (IRENA) is expecting that second-generation ethanol will have four main future markets: (i) bioethanol blended with gasoline, (ii) bioethanol for flexible fuel vehicles (FFV), (iii) bioethanol as an intermediate to other drop-in-fuels and (iv) bioethanol as an intermediate to biochemicals [81]. However, they recognize that biofuel markets are extremely complex and volatile, mostly attributed to the lack of a stable policy environment in many countries. A similar statement is made in the 2022-2031 Agricultural Outlook published by the Organization for Economic Co-operation and Development (OECD) and the Food and Agriculture Organization (FAO) [44], where it is mentioned that feedstock and crude oil prices have a lower effect on biofuels prices, compared to policies. These policies are creating an uncertainty around biofuels price projections. In the same report, future bioethanol (nominal) prices are predicted until 2031, remaining almost constant, while expecting no significant influence by cellulosic ethanol production. These estimations are based on the wholesale ethanol price data from the USA. Moreover, Panoutsou et al. [82] investigated the advanced biofuels market in the EU by 2030, identifying challenges in the market associated with appropriate pricing. Therefore, due to the lack of data, to the best of our knowledge, on second-generation bioethanol pricing in the future market and the challenges in predicting the future of this market, the average EU bioethanol price along with its projections until 2030 by the OECD-FAO Agricultural Outlook has been used in this study to benchmark the calculated MFSPs as well as calculating the cost reductions required in the break-even point analysis.

Finally, the potential of an economically viable biorefinery by 2030 was investigated, accounting for cost reductions induced by technological learning. The International Renewable Energy Agency (IRENA) has suggested a learning rate of 3% for the lignocellulosic fermentation pathway [83], while the International Energy Agency (IEA) has estimated a 5-27% reduction in the total production costs of advanced biofuels due to gained experience [78]. The Energy Information Administration of the United States, has assumed a 10-25% learning rate for capital cost reduction on cellulosic ethanol production in its 2022 Annual Energy Outlook [84]. Finally, first-generation ethanol production from corn crops is a similar technology that has been applied for many years. Based on the experience gained, a learning rate of 13% has been observed for the period of 1983 to 2005 for the United States, while 19% between 1975 and 2005 for Brazil [85].

A 3.9% learning rate for the dilute acid model of Plant L, as calculated from the single-component learning curve for the ethanol production cost is really close to the estimations made by IRENA. Indeed, all of the learning rates calculated for the large-scale biorefinery, seem to be realistic to achieve, based on both estimations for advanced biofuels as well as the experience gained from conventional biofuels. As far as Plant S is concerned, learning rates could also be possible to achieve under specific circumstances, requiring probably more investments, in order to further increase the cumulative production volume, thus allowing for a bigger cost reduction. It should be noted that in this analysis only the European cellulosic ethanol production is taken into consideration, not accounting for the global market which is much larger. For the scope of this study, which is restricted to the case study of Belgian territory, learning effects are assumed more likely to occur because of experience gained within the European region.

A bigger increase in the deployment of advanced biofuels production technology would significantly decrease the production costs, although the uncertainty surrounding the learning rates does not allow for precision in future calculations. Especially for different components the cost reduction can vary strongly. The use of the multi-component learning curve in this study proved that the difference between the learning rates for each component is significant, indicating the importance of applying the multi-component learning curve on this technology. Therefore, by applying this learning curve, the potential and contribution of each component to the cost reduction can be better assessed.

The integration of learning curves in the proposed framework allows for better estimation of the economic performance of an advanced biofuels production plant, whose large scale commercialization level is still hindered. The potential for cost reductions through learning should not be neglected, as it can provide insight on the prospects of the studied technology. The calculation of the minimum learning rates required to reach an economically viable biorefinery in the future, tackles the lack of data problem that is usually encountered in such studies and is usually criticized in literature. Furthermore, this methodology can be applied for similar FOAK technologies in the energy sector. The inclusion of the multi-factor learning curve could be investigated in future work, in order to account for the different types of learning effects.

Consequently, the large-scale biorefinery project investigated in this study seems to have a potential for investments in Belgium, by taking into consideration future cost reduction through technological learning. On the other hand, the smaller-scale bioethanol plant, relying solely on domestically produced biomass, shows a lower potential. Different valorization pathways of corn stover feedstock are recognized as an alternative option with many perspectives in the future. Biomass intermediates produced during the existing bioethanol production process, such as furfural, can be further valorised as added-value chemicals and enhance the profitability [86]. An integrated biorefinery producing biofuels in combination with multiple by-products, such as high-value biochemicals and/or biomaterials, could exhibit an improved economic performance compared to a standalone bioethanol plant.

4. CONCLUSIONS

A methodological framework for techno-economic assessments integrating learning effects has been developed, allowing for a better, fairer evaluation of the prospects of emerging

technologies. The economic feasibility of second-generation ethanol production in Belgium through the biochemical pathway was chosen as a case study. The future prospects for reaching economic viability by 2030 while accounting for cost reductions through technological learning were investigated. Two plant capacities were studied based on corn stover produced in Belgium as well as importing additional biomass. Four pretreatment methods were simulated in an integrated biorefinery plant, with a capacity of 156 kt/year dry corn stover for Plant S and 667 kt/y for Plant L. The minimum learning rates required were calculated for the single- and multi-component learning curves. The results were close to the available projections in literature for the large-scale biorefinery, reflecting the potential of such a biorefinery project in Belgium. On the other hand, the smaller capacity plant showed an overall worse economic performance, even by accounting for future cost reductions through technological learning. The dilute acid pretreatment model presented the best results, as it has already been well-developed, while the steam explosion model seems to be the alternative pathway to bioethanol production with the highest potential. Based on the current state of technology, a standalone large-scale bioethanol plant in Belgium seems to have a potential in the short future. Smaller-scale plants could also be possible by considering different valorization trajectories of corn stover into biochemicals and biomaterials, in combination with advanced biofuels.

NOMENCLATURE

Acronyms

CAPEX : Capital expenditure

COD: Chemical Oxygen Demand

FCI : Fixed capital investment

FOAK: First-of-a-kind

IEA: International Energy Agency

IPM: Interior Point Method

IRENA: International Renewable Energy Agency

ISBL: Inside battery limits

MFSP : Minimum fuel selling price

NOAK: Nth-of-a-kind

NPV : Net present value

NREL : National Renewable Energy Laboratory

NRTL: Nonrandom two liquid

OPEX: Operational expenditure

PFD: Process flow diagram

TDC: Total direct cost

TEA: Techno-economic assessment

TIC: Total indirect cost

TRL: Technology readiness level

List of symbols

C: unit cost of production (EUR/L)

C^*: unit cost of production identified from the break-even point analysis (EUR/L)

C_0: unit cost of production at an arbitrary starting point (EUR/L)

C_{EtOH}: ethanol production cost (EUR/L)

k: scaling factor

LR: learning rate

n : number of components at the multi-component learning curve

P: cumulative production (ML)

P_0: cumulative production at an arbitrary starting point (ML)

pH : pH of the pretreated slurry

Q_{EtOH}: annual ethanol production (L/y)

r: annuity factor

SF: Severity factor

T: Pretreatment temperature (°C)

t: Residence time (min)

a: learning coefficient

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APPENDIX A. SUPPLEMENTARY DATA

Supplementary data to this article can be found online: <Supplementary Material>

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