Energy Conversion and Management 87 (2014) 1195–1201

Contents lists available at ScienceDirect

Energy Conversion and Management

journal homepage: www.elsevier.com/locate/enconman

Optimal design of pre-fermentation and fermentation stages applying nonlinear programming

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ARTICLE INFO

Article history:
Available online 26 April 2014

Keywords:
Superstructure
Nonlinear programming
Fermentation
Design
Optimization

ABSTRACT

In the present work, the optimal design of pre-fermentation and fermentation operations for ethanol production is obtained developing a superstructure mathematical model. Different configurations of both operations are simultaneously considered in an overall model which also includes detailed kinetics equations. The zero wait is the transfer policy selected for these stages for ensuring the quality of these operations, given the nature and characteristics of microbiological sugary substrates. From the overall proposed model, the optimal configuration of the stages, the number of duplicated units in each stage, the size of each process unit, the process variables as concentrations and flows, and the total investment and production cost are obtained. This model is formulated as a non-linear programming problem, which is solved by the Professional Software, General Algebraic Modeling System (GAMS) with the application of CONOPT solver. The optimal design and operation of pre-fermentation and fermentation stages are obtained and the attained results are compared with the structures in conventional distillery.

1. Introduction

The production/development of a chemical (i.e. ethanol) is affected by several factors such as the raw materials used, process type (batch or continuous) and process cost. Chemical industry processes can be classified into two categories, continuous and batch processes. The continuous growth in complexity, competitiveness, and uncertainty of the market of high-added-value chemicals and food products with a short life cycle has renewed the interest in batch operations and the development of optimization models. The main advantage of batch plants in this context is their inherent flexibility to use the available resources for manufacturing relatively small amounts of several different products within the same facilities. Furthermore, batch plants can be easily reconfigured or adapted to allow modifications to production and/or cover a wide range of operating conditions within the same plant configuration.

Ethanol production is motivated by the use of renewable energy and, among bio-fuels, it is considered the most appropriate solution for short-term gasoline substitution [1]. Several countries are promoting the production of ethanol for fuel blending, but the implementation of this policy entails the expansion of existing plants and construction of new facilities. Also, the growing demand for ethanol requires search for alternative raw materials. Lignocellulosic materials, such as sugarcane bagasse, are viable alternatives for this production.

The ethanol production from lignocellulosic includes continuous and batch operations. In this paper, the focus is on batch stages, which are modeled through a superstructure where different configurations for these stages are considered. Thus, the optimal synthesis (number of units duplicated out of phase), design (unit sizes), and operation (inoculums, processing times, substrate feedings, biomass concentration, substrate concentration, etc.) for pre-fermentation and fermentation stages are simultaneously obtained in an integrated nonlinear programming (NLP) model. The model also considers detailed kinetics equations for biomass, substrate and product concentrations, which are embedded in the overall model as algebraic equations.

Finally, it is worth mentioning that these fermentation stages have long operating times, which produce long idle times and long limiting cycle times. Then, the process performance and profitability might become worse. Therefore, the objective of this paper is to show how it is possible to find out an optimal design of the stages

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http://dx.doi.org/10.1016/j.enconman.2014.04.011
0196-8904/

mentioned above at minimum cost considering simultaneously its operation.

2. Literature review

The design problem of a batch plant implies determining the plant structure, the number of units to be used at each stage and its size. Previously published works on this area resorted to mixed integer non-linear models (MINLP), where the binary variables allow contemplating the different alternatives to organize units at each stage. Several works were presented where the different process stages are modeled using fixed times and size factors. Knopf et al. [2] presented a geometric program, which was convexified in order to reach the global optimum. Yeh and Reklaitis [3] proposed an approximate sizing procedure for determining the number of units in parallel at each stage as well as its sizes for a single product batch plant. Ravemark and Rippin [4] formulated a MINLP approach for batch processes design in general while Montagna et al. [5] and Fumero et al. [6] used fixed times and size factors formulations for batch processes that specifically include fermentation stages.

On the other hand, some models used variable processing times depending on the batch size with a predetermined expression. Salomone and Iribarren [7] proposed an approach that allows optimizing design and operational decision variables simultaneously. In a later work, Pinto et al. [8] applied the formulation to fermentative processes.

A more complex representation of the unit operation requires dynamic equations for describing the process performance. Bathia and Biegler [9] proposed an NLP formulation for the design and scheduling of a batch plant considering dynamic models of processing operations. Collocation with finite elements was used for converting the differential equations into algebraic equations. They considered a simple batch plant with one unit per stage. Also, Corsano et al. [10] proposed a mathematical model involving differential equations for the process performance. These authors used a finite difference method in order to embed the dynamic equations as algebraic expressions in the overall model. They considered parallel units and unit duplication in series.

MINLP problems are usually solved through iterative methods that solve a sequence of alternate NLP subproblems with all the 0–1 variables fixed, and MILP master problems that predict lower bounds and new values for the 0–1 variables [11]. For the case of a non-convex problem, this mechanism presents the drawback that successive linearizations (master problems) usually cut part of the feasible region. In this way, some solutions to the problem are lost [12]. On the other hand, in NLP problems, the user can provide physically meaningful initializations increasing the robustness and usefulness of the optimization models. Available computer codes for solving MINLP (DICOPT for example) do not allow the user to initialize the intermediate NLP problems.

A biorefinery is a facility that integrates biomass conversion processes and equipment to produce fuels, power, and chemicals from biomass [13]. In this work, ethanol production from sugarcane bagasse is studied. Lignocellulosic biomass is the most promising feedstock considering its great availability and low cost, but the large-scale commercial production of fuel bioethanol from lignocellulosic materials has still not been implemented [14]. The conversion process for producing second-generation bioethanol, like ethanol from hydrolyzed sugar cane bagasse, is usually done according to two different approaches, generally referred to as "thermo" and "bio" pathways. Balat [14] in his review summarizes the different presented works about biofuels from lignocellulosic via biochemical pathway. On the other hand, Mohammadi et al. [15] presented an overview about thermal–chemical conversion of biomass. They investigated the utilization of gaseous substrates through a bio-catalytic route to obtain various biofuels and reported the optimum conditions for various acetogenic, hydrogenogenic and methanogenic organisms to obtain high product yields.

Ethanol production from lignocellulosic materials involves several stages (pretreatment, hydrolysis, fermentation, distillation). Various authors have referred and studied some of these stages (see the review of Cardona et al. [16]) and most of the published works about process design have dealt with fixed plant structure.

Process optimization is a challenging task in process design and the mathematical programming is an excellent tool for implementing it. Karuppiah et al. [17] addressed the heat integration problem for reducing operating cost of a bioethanol plant. They proposed a limited superstructure of alternative designs including the various process units and utility streams involved in ethanol production. Then for the optimal flowsheet, they performed a heat integration study for evaluating the energy consumption. Martin et al. [18] proposed a three stage method for optimizing the water consumption of second generation bioethanol plants. They developed a superstructure approach for the optimal conceptual design of water networks. Mele et al. [19] proposed a MILP model for the optimal design of a sugar cane/ethanol supply chain, where different process technologies are taken into account. Mathematical modeling and optimization were also applied to planning and scheduling of bioethanol processes. Grisi et al. [20] presented a MILP formulation for the short-term scheduling of the integrated processes for sugar, bioethanol, biogas and bioelectricity production. In Corsano et al. [21] a MINLP model for the simultaneous optimization of the design, operation, scheduling, and planning of a fermentation network is proposed. The optimal production campaign considering a multiperiod approach is obtained.

In this work, the integration of pre-fermentation and fermentation stages for ethanol production from molasses and hydrolyzed sugar cane bagasse is proposed. A detailed superstructure model is formulated where different decisions as the number of unit duplication, unit sizes, material flows and processing times, among others, are simultaneously considered. The superstructure consists of a set of different alternatives of unit duplication for pre-fermentation and fermentation stages. For each alternative, all the previous mentioned decisions are considered, and mass balances between both stages are stated. Taking into account that the objective function minimizes the units and operating costs, only the best structural option will be chosen, driving to zero the size of all units (and material fluxes between stages) that are not involved in the optimal structure. The presented approach is largely inspired in the superstructure optimization model presented by Corsano et al. [10]. The model was reformulated for pre-fermentation and fermentation stages using molasses and hydrolyzed bagasse. Including hydrolyzed bagasse as sugared substrate in fermentation stage is a novelty of this paper. Also, different alternatives of possible stage configurations considering units duplicated out of phase are proposed. Due to only a set of alternatives are managed in this kind of formulation, a relaxed problem is solved, and therefore this is a disadvantage of using NLP instead MINLP where all possible alternatives are simultaneously involved. Finally, unlike the work of [10], the required production is a real amount which allows comparing with the real installed ethanol plants and assessing the several tradeoff presented in the industrial practice.

3. Process description: pre-fermentation and fermentation stages

A simplified scheme of pre-fermentation and fermentation process is shown in Fig. 1. As can be observed, for each stage several

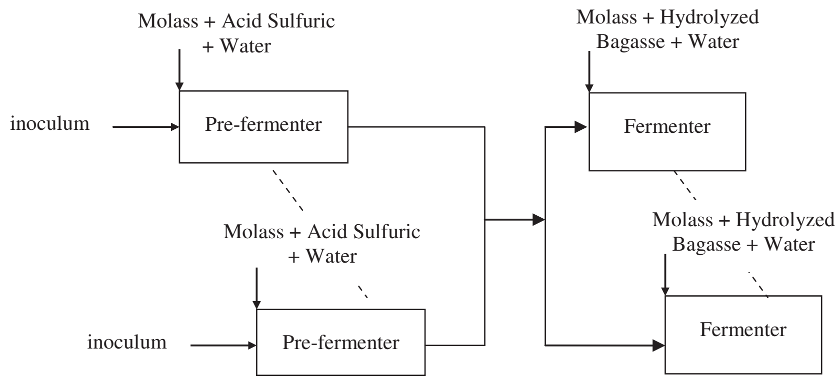

Fig. 1. Scheme of fermentative stages.

units can be duplicated out of phase in order to reduce idle times and increase process productivity. The objective of the first batch stage is the biomass production. The pre-fermenter is inoculated with a broth containing biomass. Also, molasses and acid sulfuric are added. At this stage typically large amounts of air are supplied. The metabolite production stage (fermentation) is also a batch item, fed with the biomass broth from the first stage and an appropriate fermentation blend containing molasses and hydrolyzed bagasse, both obtained from sugar cane. This stage typically works without air supply. In this work, pentoses fermentation is not considered because they are used for furfural production (a process by-product). Furthermore, this type of fermentation requires glucose separation and specific microorganisms for performing it. The pretreatment step that allows obtaining furfural is not addressed in the paper, since it is out of the scope of this work. In other words, glucose fermentation from molasses and hydrolyzed bagasse is only considered.

For each proposed stage configuration, mass balances, feeding constraints and interconnection constraints between pre-fermentation and fermentation stages are modeled. The dynamic equations are modeled by discretizing them using a numerical method based on finite differences. The total produced amount of ethanol (kg h^{-1}) at the final fermentation stage is a model parameter fixed according to the designer criteria. The objective function is the minimization of the total investment and operation costs, i.e. equipments cost and raw material cost. As a result of the optimization, the interconnection fluxes and unit sizes for some configuration alternatives are zero. This means that those alternatives are not selected as the optimal one. The optimal stage configuration is that with nonzero unit sizes and material flows between both stages. Although the required production can be reached with different stage configurations, due to economies of scale, the optimal solution selects only one alternative for each stage. If more than one alternative is allocated, the investment cost is increased and therefore the objective function is worsened. In this way, the overall model is formulated without resorting integer variables, since the alternatives are managed as non-linear programming formulation. As previously mentioned, since a reduced number of alternatives is considered, the formulation represents a relaxed problem compared with a full space MINLP formulation.

4. Mathematical model

4.1. Mass balances for each stage

The mass balances of both stages are described by the following differential equations according to Chekhova et al. [22] and Nielsen et al. [23]. Eq. (4) is not considered for pre-fermentation stage since in this stage only biomass is produced.

$$\text{Biomass}: \frac{dX_{pa}}{dt} = \mu_{pa}X_{pa} - \upsilon_{pa}X_{pa} \tag{1}$$

$$\text{Substrate}: \frac{dS_{pa}}{dt} = -\frac{\mu_{pa}X_{pa}}{Yx_{pa}} \tag{2}$$

$$\text{Non-active biomass}: \frac{dXd_{pa}}{dt} = \upsilon_{pa}X_{pa} \tag{3}$$

$$\text{Product}: \frac{dE_{pa}}{dt} = \frac{\mu_{pa}X_{pa}}{Ye_{pa}} \tag{4}$$

$$\text{where} \quad \mu = \mu_{\max,pa}\frac{S_{pa}}{ks_{pa} + S_{pa}} \tag{5}$$

The subscript p refers to the pre-fermentation or fermentation operation ($p = 1$ and $p = 2$ respectively), while a is related to the configuration alternative selected from the superstructure (number of units duplicated out of phase for each stage), $a \in A_p$, A_p the set of different alternatives for p. X is biomass concentration (kg/m^3), S is substrate concentration (kg/m^3), Xd is non-active biomass concentration (kg/m^3) and E is ethanol concentration (kg/m^3). The specific rate of growth μ used in this paper is described by [22–23].

$\mu_{\max}$ (maximum specific rate of growth), ks (saturation constant) and υ (dead rate constant of microorganisms) are model parameters taking different values according to the pre-fermentation and fermentation stages. The biomass/substrate (Yx_{pa}) and product/substrate (Ye_{pa}) yields were obtained from elementary balances of microorganism growth in pre-fermentation and product formation in fermentation. Chirino [24] developed these elementary balances in reactions obtaining Yx_{pa} = 5.8 mol cellule/mol substrate (maximum value in pre-fermentation) and Ye_{pa} = 1.99 mol ethanol/mol substrate (maximum value in fermentation). These values will be used as model parameters in this paper.

The above equations are discretized using the trapezoidal method [25]. In this way, the resulted algebraic equations are embedded in the overall mathematical model and they are simultaneously solved. For more details of this method and its application, review the work of Corsano et al. [26]. Also, in that work the robustness of the method and the comparison with simulation approaches are stated.

4.2. Mass balances between stages

The pre-fermenters are fed with inoculums and a blend of molasses, water and sulfuric acid (Eq. (6)). After its processing, the fermented broth is passed to the fermentation stage. In addition, each fermenter is fed with molasses, water and hydrolyzed bagasse (Eqs. (7) and (8)). The following equations describe these mass balances:

$$V_{inoc,a} + M_{pre,a} + W_{pre,a} + SA_{pre,a} = V_{pre,a} \quad \forall a \in A_{pre} \tag{6}$$

$$\sum_{a\in A_{pre}} V_{pre} + \sum_{a\in A_{fer}} FEED_{fer,a} = \sum_{a\in A_{fer}} V_{fer,a} \tag{7}$$

$$M_{fer,a} + W_{fer,a} + HB_{fer,a} = FEED_{fer,a} \quad \forall a \in A_{fer} \tag{8}$$

where V_{inoc} is the inoculums volume, M_{pre}, M_{fer}, W_{pre}, and W_{fer} is the molasses and water volume added to pre-fermentation and fermentation respectively, SA_{pre} is the volume of sulfuric acid added to the pre-fermenter, HB_{fer} is the hydrolyzed bagasse volume, and V_{pre} and V_{fer} represent the pre-fermenter and fermenter volume. $FEED_{fer}$ is the blending of substrates added to the fermenters. The subscript a refers to the configuration alternative in the superstructure.

The model also considers the mass balances for each component:

$$\sum_{a\in A_{pre}} X^{fin}_{pre,a} V_{pre,a} = \sum_{a\in A_{fer}} X^{ini}_{fer,a} V_{fer,a} \tag{9}$$

$$\sum_{a\in A_{pre}} Xd^{fin}_{pre,a} V_{pre,a} = \sum_{a\in A_{fer}} Xd^{ini}_{fer,a} V_{fer,a} \tag{10}$$

$$\sum_{a\in A_{pre}} S^{fin}_{pre,a} V_{pre,a} + \sum_{a\in A_{fer}} S_{feed,a} FEED_{fer,a} = \sum_{a\in A_{fer}} S^{ini}_{fer,a} V_{fer,a} \tag{11}$$

The subscript *pre* and *fer* refer to pre-fermenter and fermenter respectively, while the superscript refers to the initial (at the beginning of the processing) or final (at the end of the processing) concentration. The substrate concentration for the fermenter feeding is given by:

$$M_{fer,a} S_{molass} + HB_{fer,a} S_{HB} = FEED_{fer,a} S_{FEED,a} \quad \forall a \in A_{fer} \tag{12}$$

The initial substrate concentration for pre-fermentation stage depends on the feeding of substrate:

$$M_{pre,a} S_{molass} = V_{pre,a} S_{FEED,a} \quad \forall a \in A_{pre} \tag{13}$$

Since the ethanol is produced at fermentation stage, the initial product concentration is equal to $0\ \mathrm{g\,l^{-1}}$, i.e. $E^{ini}_{fer,a} = 0$. The formation of ethanol is given by Eq. (4).

Finally, the required production has to be fulfilled at the end of the fermentation process. As all possible configurations for fermentation stages are simultaneously considered, then the total production is obtained from the sum of all alternatives proposed in the superstructure model:

$$Prod = \sum_{a\in A_{fer}} \frac{E^{fin}_{fer,a} V_{fer,a}}{CT} \tag{14}$$

where Prod represents the total amount (kg/h) of ethanol produced at fermentation stage, CT is the cycle time of the plant, and $E^{fin}_{fer,a}$ is the final ethanol concentration. It is worth noting that only one alternative proposed in the superstructure will be active (unit sizes different to zero) in the optimal solution, and therefore, the total production will be reached according to that fermentation stage configuration and design.

4.3. Timing constraints

The Zero-Wait (ZW) transfer policy considers that a processed batch is immediately transferred to the following stage. Because of biomass degradation during idle times of the units, the best transfer mode for this type of production is ZW.

For this policy, we will consider the use of out of phase parallel units. In this case, the plant cycle time is equal to the maximum of the stage processing time divided by the number of parallel units at this stage. Let $t_{pre,a}$ and $t_{fer,a}$ be the processing times, which are optimization variables, for pre-fermentation and fermentation stages respectively for each alternative a in the superstructure. Then,

$$CT = \max_{\substack{a\in A_{pre}\\ a\in A_{fer}}} \left\{ \frac{t_{pre,a}}{M_{pre,a}}, \frac{t_{fer,a}}{M_{fer,a}} \right\} \tag{15}$$

where $M_{pre,a}$ and $M_{fer,a}$ represents the number of parallel units duplicated out of phase for pre-fermentation and fermentation stages respectively. $M_{pre,a}$ and $M_{fer,a}$ are obtained from the superstructure presented below.

In order to avoid a discontinuous NLP, the "max" function is replaced by "$\geqslant$" in Eq. (15):

$$CT \geq \frac{t_{pre,a}}{M_{pre,a}} \quad \forall a \tag{15a}$$

$$CT \geq \frac{t_{fer,a}}{M_{fer,a}} \quad \forall a \tag{15b}$$

4.4. Pre-fermentation and fermentation superstructure

The number of alternatives proposed for each operation p, $p \in \{pre, fer\}$, is selected after analyzing the actual ethanol production facilities from molasses in Cuba (for the production of 500 hl/d [27,28]). In both previous works, the plant taken as reference has three pre-fermenters of capacity equal to $15\ \mathrm{m^3}$, which are fed with molasses and filter juice. Also, for fermentation stage, there are eleven fermenters operating out of phase, with capacity equal to $100\ \mathrm{m^3}$ each.

For the pre-fermentation, three possible configurations are considered: one, two, and three units duplicated out of phase. For the fermentation, three alternatives are considered: 8, 10 and 12 units in parallel out of phase respectively.

Then, according to these configurations, the superstructure involves the model parameters presented in Table 1. Fig. 2 shows these alternatives and some of the involved decision variables. Therefore, the model considers simultaneously all these alternatives in all the mass balances previously described and in the objective function presented below.

4.5. Objective function

The objective function is total annual cost minimization given by investment cost and operative cost. For the investment cost, unit sizes are considered, while for operative cost, the cost of feeding substrates and nutrient are taken into account [29,30]:

Table 1
Superstructure characteristic in pre-fermentation and fermentation stages.

	Pre-fermentation	Fermentation
Alternative 1	$M_{pre,a1} = 1$	$M_{fer,a1} = 8$
Alternative 2	$M_{pre,a2} = 2$	$M_{fer,a2} = 10$
Alternative 3	$M_{pre,a3} = 3$	$M_{fer,a3} = 12$

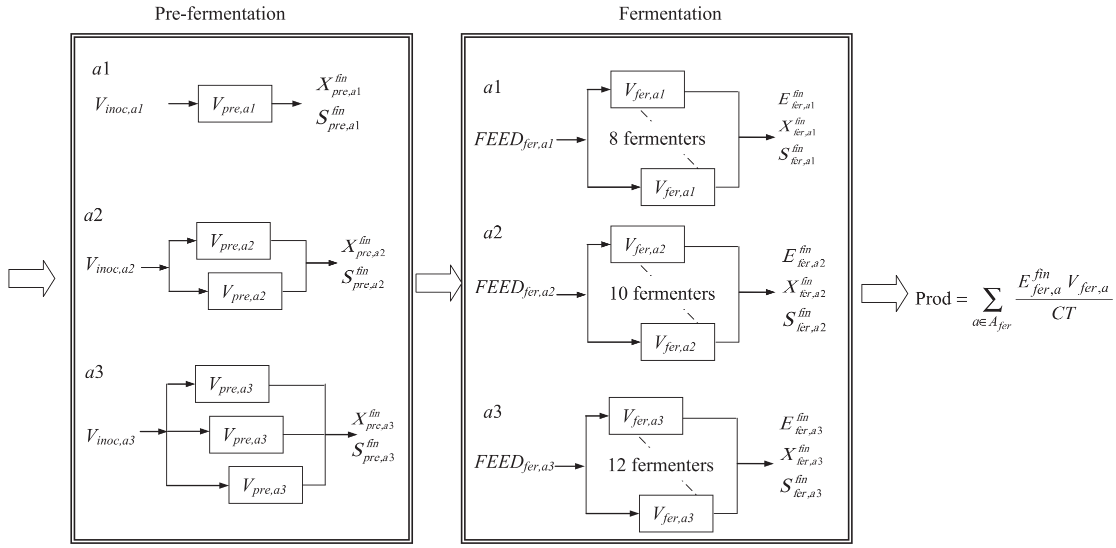

Fig. 2. Proposed superstructure and some decision variables for pre-fermentation and fermentation stages.

$$\mathrm{Min}\left\{C_{ann}\sum_{a\in A_p}\alpha_p M_{pa} V_{pa}^{\beta_p} + \frac{HT}{CT}\sum_{a\in A_p}\sum_{f\in feed} Cf_f Vf_{fpa}\right\} \tag{16}$$

where C_{ann} is a constant that annualizes and actualizes the investment cost considering also the equipment depreciation, Vf_{fpa} represent the amount of sugaring substrate used at each alternative $a \in A_p$, with $p = pre, fer$, and Cf its unit cost.

The cost exponent values β were taken from [31] for vertical fermenters. The cost coefficients α were taken from [32] updated by [33] and [34] for years 1995 and 2013 respectively.

In summary, from the optimization of the presented mathematical model, the configuration of each stage and the unit sizes, the feeding substrates and nutrient for each stage, the processing time for each operation, the limiting cycle time, and the total annualized cost are simultaneously obtained.

5. Results

The proposed model was formulated and solved in GAMS [35] on an Intel Core i7, 3.4 GHz processor, and 8 GB of RAM, using CONOPT solver for solving the NLP problems. The time horizon was fixed to 7200 h year^{-1} (300 days year^{-1}) and the ethanol production to 500 hl day^{-1}. In Table 2, some of the main model parameters for units kinetic and costs are shown, while the substrate and nutrients costs are presented in Table 3.

The optimal solution selects alternative 2 for pre-fermentation stage and alternative 1 for fermentation stage. Design, configuration and processing time for both stages are shown in Table 4.

As can be seen from Table 4, two pre-fermenters and eight fermenters out of phase are used. The sugaring substrates used in each stage and the inoculums added to pre-fermentation stage are depicted in Fig. 3.

The cycle time is equal to 3 h, i.e. a batch of ethanol is obtained from fermentation stage each 3 h (without considering the start up of the process, in other words, the first batch). This reduces considerably the huge idle times that frequently occurs due to long fermentation processing times. Fig. 4 shows the Gantt chart for this solution. It can be observed from the Figure that pre-fermentation units have idle times.

The total annual cost is equal to $7,576,322. An itemized list of cost is presented in Table 5. From that Table, it can be obtained that the unitary production cost is equal to 50.5 $ hl^{-1}. Considering that the produced ethanol is a technical alcohol and its selling price is equal to 60 $ hl^{-1}, then the net annual profit considering pre-fermentation and fermentation stages is $1,423,677.

The model involves 731 constraints and 757 continuous variables, and the resolution time is equal to 0.3 s.

Table 2
Model parameters for pre-fermentation and fermentation stages.

Parameters	Value	UM
$\mu_{\max,pre}$	0.461	h^{-1}
$\mu_{\max,fer}$	0.1	h^{-1}
Yx_{pre}	5.8	mol cellules/mol substrate
Ye_{fer}	1.99	mol ethanol/mol substrate
ks	25	mg l^{-1}
α_{pre}, α_{fer}	46,000	–
β_{pre}, β_{fer}	0.52	–

Table 3
Substrates and nutrients cost.

Substrate and/or nutrient	Value ($/ton)
Bagasse hydrolyzed	343.80
Molasses	64.80
Water	0.05
Antifoaming	225.00
Sulfuric acid	100.00
Urea	390.00
Nutrients	9.28

Table 4
Optimal configuration and processing times.

p	M_p	Processing time (h)	Size (m^3)
Pre-fermentation	2	2.9	40
Fermentation	8	24	123.28

6. Discussion

The stage configurations and unit sizes obtained by the proposed approach are very similar to that presented in the literature about Cuban distilleries [27,28,36]. However, in those works the

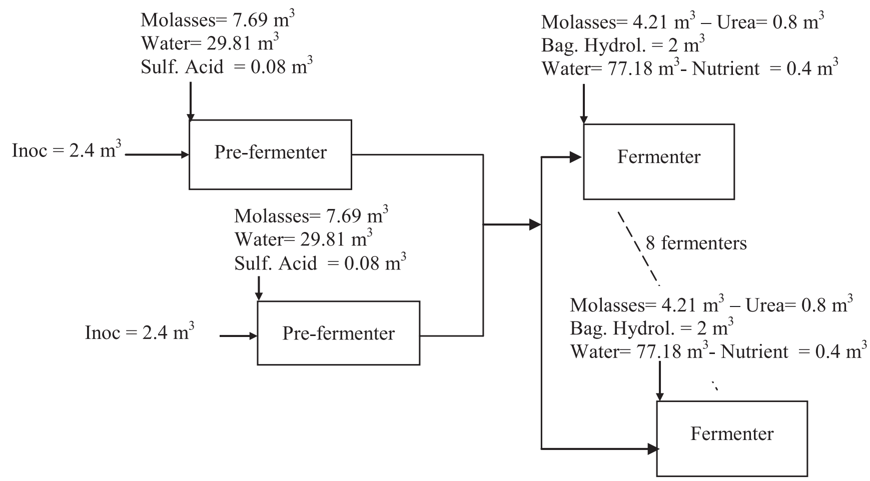

Fig. 3. Optimal design and substrate feeding.

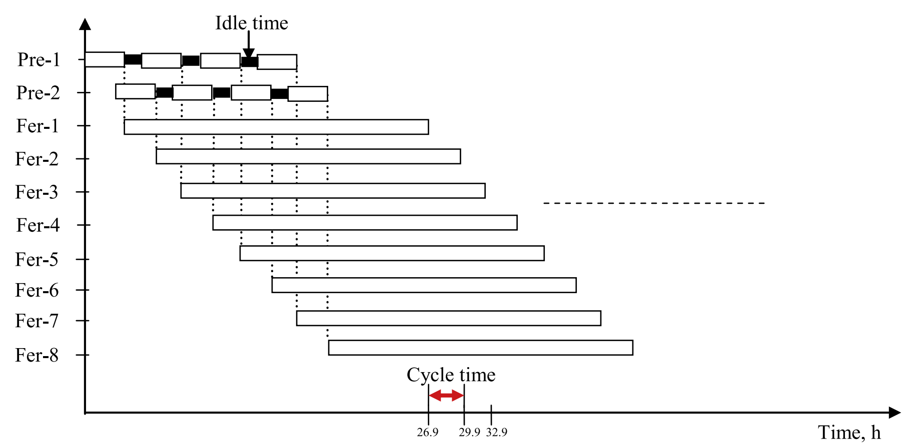

Fig. 4. Gantt chart for the optimal ethanol production planning.

Table 5
Economical results expressed in \$ year^{-1}.

Cost	Value
Investment cost	1,772,488.8
Substrate-nutrients cost	5,803,833.6
CTP annual	7,576,322.4

total cost is near 10–20% increased compared with the total cost given by the presented work (\$55–60 vs. \$50 per hl of ethanol). This is due to the use of a superstructure model which allows obtaining simultaneously the optimal configuration, unit sizes and operative variables. In the presented approach the processing times are operating variables which are jointly obtained with design variables. Therefore, idles times are reduced and equipment efficiency is improved. Also, hydrolyzed bagasse is utilized as sugaring substrate instead of filter juices, which improves the fermentation yields. It is worth mentioning that in the total cost, bagasse is considered. This cost can be eliminated if hydrolysis process is integrated into fermentation model. In this way the total cost is reduced. This constitutes a future work.

It is worth highlighting that the optimal solution not only provides the optimal configuration and design of pre-fermentation and fermentation stages for ethanol production but it also gives the production planning over the time horizon and the detailed operational conditions as processing times and substrates needed for the feeding. Therefore, this work enables to assess the trade-offs between the different design and operating variables involved, providing a tool for the analysis of preliminary design of fermentation networks.

7. Conclusions

A NLP model was presented for the simultaneous optimization of the design and operation of pre-fermentation and fermentation stages for ethanol production. Hydrolyzed bagasse is used as fermentation feeding and detailed mass balances are considered in the formulation. The optimal processing times are simultaneously obtained with plant configuration (number of units duplicated for each stage). Therefore, the limiting cycle time is jointly optimized with processing variables. In this way, the processes performance is improved compared with models with fixed operating times for which the limiting cycle time has to be adjusted to those times.

The approach represents a tool for analyzing different plant configuration and operation. This work was focused on bioethanol production from hydrolyzed bagasse and molasses but the approach also serves as a tool for evaluating different scenarios considering different raw materials, or for analyzing scenarios with fluctuations in cost, demands, production targets, etc.

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