# Risk-Conscious Optimization Model to Support Bioenergy Investments in the Brazilian Sugarcane Industry

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**Abstract**

The past decades have seen a diversification of the sugarcane industry with the emergence of new technology to produce bioenergy from by-product and waste process streams. Given Brazil's ambitious goal of reducing green-house gas emissions by over 40% below 2005 levels by 2030, it is of paramount importance to develop reliable decision-making systems in order to stimulate investment in these low-carbon technologies. This paper seeks to develop a more accurate optimization model to inform risk-conscious investment decisions for bioenergy generation capacity in sugarcane mills. The main objective is for the model to enable a better understanding of how Brazilian government policies, such as the electricity price in the regulated market, may impact these investments, by taking into account the uncertainty in sugar, ethanol and spot electricity markets and the interdependency between production and investment decisions in terms of saleable product mix. The proposed methodology combines portfolio optimization theory with superstructure process modeling and it relies on simple surrogates derived from a detailed sugarcane plant simulator to retain computational tractability and enable scenario analysis. The case study of an existing sugarcane plant is used to demonstrate the methodology and illustrate how the model can assist decision-makers. In all of the scenarios assessed, the model recommends investment in extra bioelectricity capacity via the anaerobic digestion of vinasse but advises against investment in second-generation ethanol production via the hydrolysis of surplus bagasse. Furthermore, the decision to upgrade the cogeneration system with a condensation turbine is highly sensitive to the electricity price practiced in the regulated market, capacity constraints on the sugar-ethanol mix, and the accepted level of risk. Another key insight drawn from the case study is that recent market conditions have favored a production focused on the sugar business, making it challenging for policy-makers to create attractive scenarios for biofuels. Long-term electricity contracting appears to be the main hedging strategy for de-risking other products and investments in the sugarcane business, provided it is priced adequately.

*Keywords:* sugarcane plant, renewable energy, poly-generation, portfolio optimization, superstructure

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modelling, scenario-based analysis

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## 1. Introduction

Low-carbon energy systems are under development worldwide to displace fossil fuels, which are responsible for the bulk of carbon dioxide ($CO_2$) and other greenhouse gas (GHG) emissions that contribute to climate change. The participating countries in the recent Paris Agreement [1] have committed to so-called nationally determined contributions (NDCs), with a view to mitigating climate change and adapting to its effects. Despite presenting one of the largest shares of renewable energy in the world already, Brazil is committed to reducing GHG emissions by 43% below 2005 levels in 2030. In the energy sector, Brazil intends to achieve 45% of renewables in the energy mix by 2030 [2].

As a result of multiple incentive programs the Brazilian government has supported since the 1970s [3], the sugarcane sector currently holds the largest share (17%) among all renewables in the national energy mix [4], while still showing a significant potential for expansion through alternative technological routes. Clearly this sector will continue playing a major role as supplier of biofuel but it might be called upon to play a prominent role as supplier of electrical power too.

While the processes for sugar and ethanol production have now reached a high level of technological maturity, a number of prospective routes to increase energy generation from by-product and waste process streams have recently emerged. For instance, bagasse—the fibrous residue from the sugarcane juice extraction process—may be exploited in many ways. A large body of research has explored new economically feasible uses of bagasse, including improved combined heat and power (CHP) systems [5, 6], and for the production of second-generation (2G) ethanol [7–9] and biogas [10]. The use of vinasse—the bottom product of the ethanol distillation process—for biogas generation has also been investigated [11–13] instead of their traditional use in fertirrigation of sugarcane plantations. But despite the advances promised by these new technological routes, the number of new bioelectricity projects has dropped significantly over the past few years [14]. Such disinterest is partly attributed to the fact that investments in renewable energy generation are costly. But there is also large uncertainty regarding returns on investment as the sugar, ethanol and electricity markets have been historically volatile. Given the ambitious NDC target of reducing GHG emissions by more than 40% below 2005 levels over the next decade, it is of paramount importance to develop reliable decision-making systems that can advise policy-makers in order to regain investors' trust. The methods and tools developed in Process Systems Engineering (PSE) can be a great help in this context.

Systematic optimization methods based on so-called process superstructure models have proven particularly valuable for the synthesis and design of energy systems, including bioenergy production systems; see the recent survey and methodological papers [15–20]. A superstructure model describes a set of candidate process pathways, both the process units and the interconnections; then, the optimizer is in charge of selecting the best possible pathways in the sense of one or several criteria, for instance maximizing economic performance or minimizing environmental impact. A major emphasis in PSE has been accounting for uncertainty, such as uncertain demands or market conditions, as part of the process synthesis and design exercise. A common approach to assessing the effect of uncertainty in a selected process pathway entails a scenario analysis (e.g. using Monte Carlo sampling [21, 22]) but this approach cannot be used for screening optimal process pathways. Instead, a large body of research has been devoted to integrating uncertainty directly into the superstructure optimization model. Either a robust or a stochastic optimization formulation may be adopted depending on the description of the uncertainty in terms of simple bounds or by means of a probability distribution and whether the objective is to optimize an average or worst-case scenario [15–17]. In order to de-risk the solutions one may also want to account for potential shortfalls [23, 24] or regret [25] alongside the other design criteria, for instance using a multiobjective optimization approach. Such superstructure optimization models for risk-conscious decision-making under uncertainty are well developed and have been used for decision-making in various (bio)energy sectors, including CHP systems [20, 26, 27], distributed energy systems [28], and bioethanol supply-chains [29, 30].

Concerning the sugarcane sector, a growing number of optimization-based assessments have been reported in the literature that consider the integration of new bioenergy processes into traditional sugarcane plants, in the form of 2G ethanol production or bioelectricity from bagasse. Many such assessments [e.g. 9, 31–34] failed to account for market price uncertainty, although they concluded to a high sensitivity of the optimal decisions toward the electricity and ethanol prices. They furthermore assumed no sugar production in the sugarcane mill, despite the fact that the vast majority of the processing plants in Brazil operate with an integrated sugar-ethanol process [35] and the recent market conditions have been more favorable to sugar production. Other assessments [e.g. 5, 8] were conducted under the assumption of a fixed production mix, even though production decisions in industrial practice are usually based on market conditions at the beginning of each crushing season with a view to maximizing a sugarcane mill's profits. These production decisions are furthermore concomitant with investment decisions, since introducing a new energy recovery process will often modify a plant's overall energy balance on an annual basis [9, 36]. Finally, a number of optimization-based assessments allowed for a variable product mix [10, 37–39], yet without accounting for the risk incurred by price variability on the decision to invest in new technologies to increase power production. Despite their limitations, all of these assessments have been instrumental in establishing that sales of surplus electrical power could increase profits significantly and in highlighting the role of the Brazilian regulated market of electricity in incentivizing these sales.

The present paper seeks to develop a new optimization model to inform risk-conscious investment decisions on bioenergy generation capacity in sugarcane mills. A key objective is for the model to enable a better understanding of how electricity prices in the Brazilian regulated market may impact such investments, taking into account the uncertainty in sugar, ethanol and electricity markets and the interdependent production and investment decisions in terms of saleable product mix. The methodological novelty lies in the application of a portfolio optimization strategy [40] based on historical price series to de-risk decisions, in combination with superstructure process modeling to describe a range of technological options; an approach that has not been pursued in sugarcane plants thus far. The superstructure model furthermore embeds simple surrogate models [41] derived from a detailed process simulator of the sugarcane mill to retain computational tractability and enable a comprehensive scenario analysis. A case study is conducted for an existing sugarcane mill to demonstrate the methodology and illustrate how the model can assist in the decision-making process from both the producer and the policy-maker viewpoints.

The rest of this paper is organized as follows: Background on prospective bioenergy generation technologies and decision-making in the sugarcane industry is presented in Sec. 2. Next, the optimization model and the methodology are described in Sec. 3. The results of a case study are presented and analyzed in Sec. 4. Finally, concluding remarks are drawn in Sec. 5.

## 2. Background

The sugarcane industrial process starts with sugar extraction from the shredded sugarcane stalks. The extracted juice is treated in order to remove impurities, and the clarified juice is then shared between the ethanol distillery and the sugar factory. The fibrous residue from the sugarcane juice extraction, known as bagasse, has an important use in CHP systems to cover the demands for steam and electricity of the plant. It is noteworthy that all of Brazil's sugarcane plants are self-sufficient in thermal, mechanical and electrical energy. However, the majority of these plants run low efficiency systems based on Rankine cycles, which limits the surplus power they may generate [5, 7]. The bottom product of the ethanol distillation process, known as vinasse, is comprised of residual amounts of sugar, alcohol and heavier volatile compounds. This nutrient-rich residue can be used for fertirrigation of sugarcane plantations, subject to environmental legislations in order to limit soil contamination; the Regulation P4.231 in São Paulo state, Brazil [42]. For further details about sugarcane industrial processes, refer to [e.g. 3, 43–45].

### *2.1. Prospective technological routes to bioenergy generation*

Driven by an increasing valuation of bioelectricity in the Brazilian market, a growing body of research is applying systems thinking to develop and assess bioenergy production systems in sugarcane mills. Ensimas et al. [5] analyzed the potential for steam demand reduction in sugar and ethanol processes. They also evaluated four co-generation systems in sugarcane plants: a traditional Rankine (steam) cycle with a back-pressure turbine; a steam cycle with condensation-extraction turbine; and two configurations based on biomass gasification. All four systems were compared for a fixed 50%-share of juice between the sugar and ethanol processes. Ensimas et al. found that a steam cycle with condensation-extraction turbine could significantly increase the surplus electricity generation in plants with reduced steam demand. A further benefit of this co-generation system was a higher flexibility toward power generation, including the possibility of producing electricity during the non-crushing season. With a traditional Rankine cycle, the sugar process dictates the quantity of steam that can be produced by the boiler and so the co-generation system can only operate during the crushing season [5].

Dantas et al. [6] compared three investment options to allow for a more efficient use of bagasse: a steam cycle with condensation-extraction turbine to increase power capacity; a system of combined cycle turbines using syngas from bagasse gasification; and a 2G ethanol production system. Like Ensimas et al., they identified steam cycle with condensation turbine as the best investment option for extra power generation.

Dias et al. [8] developed a flexible biorefinery concept for processing lignocellulosic residues (sugarcane trash and bagasse) into bioelectricity and 2G ethanol. They assessed three scenarios, wherein (i) all of the surplus residues are used for 2G ethanol production, (ii) half of the surplus residues are used for 2G ethanol production and the other half for electrical power generation, or (iii) flexible use of the surplus residues is decided based on market conditions in each season. The last two scenarios assumed that a steam cycle with condensation turbine was installed, whereas the first scenario assumed a traditional Rankine cycle with the back-pressure turbine. Their results predicted that the flexible biorefinery concept would enable a faster return rate. But the result analysis also revealed a high sensitivity toward changes in ethanol price which could render the first scenario of 2G ethanol production from bagasse more advantageous if the prices practiced for ethanol in Brazil were to increase moderately in the future. Despite a growing number of scientific reports arguing in favor of 2G ethanol from bagasse [7, 9], this technology is still deemed uneconomical for use at industrial scale.

Another prominent investment option that has gained popularity in recent years is concerned with the use of vinasse for biogas generation using anaerobic digestion, followed by fertirrigation of the digested vinasse. The penetration of this technology so far has been hindered by the lack of valorization of biogas as a fuel and the fact that fertirrigation with raw vinasses remains a well-accepted practice [13]. Raw vinasses have a high organic content that can lead to soil degradation in the long run and give rise to air emissions. The anaerobic treatment reduces the organic content while maintaining their inorganic nutrient content but the use of high doses of Na-based alkalizing compounds can impede the land disposal of certain digested vinasses [46]. Understanding the environmental pros and cons of fertirrigation using either raw or digested vinasses remains an active research area. From a techno-economic standpoint, Salomon et al. [11] compared four applications of biogas from vinasse for power generation and identified reciprocating combustion engines (RCE) as the most suitable technological option. They also discussed scenarios under which power generation from vinasse with RCE could be economically viable. Interestingly, Pazuch et al. [12] pointed out in a later study that the additional revenue from commercializing the surplus bagasse that would be freed if biogas was used to supply the internal power demand could already make this investment viable. The results by Moraes et al. [13] agree on the fact that considerable surplus power production could be generated using anaerobic digestion of vinasse, comparable in scale to the surplus power derived from bagasse processing for certain mills.

A third potential biomass resource consists of the fiber in the sugarcane leaves and tops, known as straw or trash. The practice of burning straw has been mostly replaced by a system called green cane management across Brazil, whereby large amounts of plant litter are deposited on the soil after each harvest. Agronomic benefits of such a straw blanket include nutrient recycling, reduction of water losses, inhibition of weed growth, and soil protection against erosion, to name but a few [47]. A growing number of reports [47, 48] suggest that part of the lignocellulosic material left on the ground could be recovered and used for energy production in sugarcane mills, thus improving the overall energy balance. However, understanding and quantifying the agronomic, environmental and economic impacts of straw deposition versus recovery remains an active research area but beyond the scope of this paper. Therefore straw recovery is not considered as part of the technological pathways hereafter.

### *2.2. Need for reliable decision-making in the Brazilian sugarcane sector*

The technology survey in the previous section shows that prospective routes to increase energy and power generation in sugarcane plants are plentiful, albeit at different readiness levels. In practice the decision of whether or not to invest in new energy or power generation capacity is complicated by several factors.

First of all, there is large uncertainty on the return on investment as the sugar, ethanol and electricity markets have been historically volatile. These variations are observed both during an annual season and between different seasons, with causes ranging from adverse weather conditions and crop failure in a given region or in other production countries, to changes in the global economy. Oftentimes the prices of sugar, ethanol and spot electricity also exhibit (direct or inverse) temporal correlations, possibly with a lag time.

Secondly, production decisions in the sugarcane sector mainly revolve around using the biomass resources in order to maximize profits during the coming season. The foremost production decisions have historically been concerned with the shares of sugar and ethanol productions. But with the installation of energy recovery capacity from waste and by-product process streams on a plant, the overall availability of surplus bagasse and vinasse becomes dependent on the chosen shares of sugar and ethanol. This could have large repercussions on the plant's revenue, and therefore should be factored in to the decision to invest in new energy or power capacity.

Thirdly, there are two contracting environments for electricity commercialization in Brazil [49, 50]: the regulated market (ACR – *Ambiente de Contratação Regulada*), wherein prices are defined by the Brazilian Electrical Energy Commercialization Chamber (CCEE – *Câmara de Comercialização de Energia Elétrica*) through auctions and are guaranteed by long-term contracts—usually 20 or 25 years for biomass; and the free market (ACL – *Ambiente de Contratação Livre*), which consists of bilateral contracts between a producer and a large consumer whose specific terms and conditions are not disclosed to the public—including the negotiated electricity price and the contract duration which is typically between 6 months and 6 years [51]. There is finally a short-term, weekly spot market (PLD – *Preço de Liquidação de Diferenças*), used by the CCEE to settle differences between actual production/consumption and contracted amounts in both the regulated and free markets; but unlike other spot markets around the world, there is no short-term energy trading taking place in the Brazilian market. In addition to making investment decisions, sugarcane producers must therefore decide whether and how much electrical power they want to commit to either the free market or the regulated market, keeping in mind the vast differences in terms and conditions between them. Currently in the state of São Paulo, 53% of the sugarcane mills that produce surplus electricity sell exclusively to the free market, while only 9% sell exclusively to the regulated market, the remaining 38% selling electricity to both markets [52].

Given these high levels of flexibility and uncertainty, basing decisions on average scenarios and expected prices would inevitably lead investors to make risk-inclined decisions, potentially causing serious shortfalls. It is thus critical to develop reliable, risk-conscious decision-making systems in order to identify bottlenecks and opportunities in the sugarcane business, and help policy-makers to devise incentive programs.

Several recent studies have focused on developing optimization models in response to this need. Grisi et al. [37] developed an optimization model that decides the product mix in order to maximize profit in a sugarcane mill. They concluded that the electricity prices practiced in Brazil's free and regulated markets are not sufficiently attractive to justify surplus electricity generation. Yet an important limitation of their model was that it did not account for the variations in sugar, ethanol and free market electricity prices, nor did it consider investment in prospective technological routes to improve energy recovery from waste and by-product streams, thereby shedding doubts on the insight drawn. The model developed by Carpio and Souza [38] uses portfolio theory [40] to decide the optimal allocation of surplus bagasse for power generation, to be sold in either the free or the regulated market, and/or for 2G ethanol production. Dutenkefer et al. [10] also developed a robust portfolio optimization model to assess the benefits of inserting biogas into the product mix of sugarcane mills, while Oliveira et al. [39] applied portfolio optimization to decide on hedging strategies for sugar and ethanol possibly involving storage decisions during the season. However, investment in new energy or power generation capacity was not considered in any of these recent studies; nor was the interrelation between decision regarding surplus energy or power generation from waste streams and decisions about sugar and ethanol shares in sugarcane mills.

This literature survey justifies the main objective of the present paper to develop a new optimization model that can inform risk-conscious investment decisions on bioenergy generation capacity in sugarcane mills, by taking into account the uncertainty in sugar, ethanol and free electricity markets and the interrelation between production decisions in terms of the final product mix. The overall methodology and model formulation are presented in the following section.

## 3. Methodology

Superstructure optimization [17, 53] is a natural approach to selecting among various process configurations alongside key design and operational parameters. This approach has been successfully applied to process synthesis and design problems in various areas, including integrated process water networks [54, 55], wastewater resource recovery [56, 57], biorefineries [58–60], and even sugarcane processing [31, 61]. However, simple enough models of the units participating in a superstructure are typically required in order for such superstructure optimization problems to be computationally tractable. The use of surrogate models has been gaining popularity in this context [41], e.g. in the form of linear, piecewise linear or polynomial input-output relationships.

Herein, we consider a set of basic steady-state mass balances as backbone for the superstructure model (Sec. 3.1). We assume constant conversions in the sugar and ethanol production processes as well as in the bagasse processing, vinasse treatment, biogas production and power production units. Interactions between these units are captured via surrogate models that describe the effect of product-mix decisions on both the yearly power generation and 2G ethanol production from surplus bagasse. Later we use data generated with the Open Sugarcane Process Simulation Platform [36]—a detailed process simulator developed for the economic assessment of bioenergy projects in sugarcane mills—to obtain the conversion values and the surrogate models in the form of piecewise-linear relationships. The complete superstructure model is embedded as constraints into a multiobjective portfolio optimization problem (Sec. 3.2) which computes optimal, risk-conscious, annual production-mix and investment decisions under market uncertainty.

### *3.1. Sugarcane plantwide modeling*

A generic superstructure of the sugarcane mill process is presented in Fig. 1, based on the technology review conducted in Sec. 2.1. The units in this superstructure comprise the sugarcane milling ($\mathsf{mill}$), sugar factory ($\mathsf{fact}$), ethanol distillery ($\mathsf{dist}$), treatment of vinasse residues ($\mathsf{treat}$), and cogeneration system using a traditional Rankine cycle with back-pressure turbine ($\mathsf{rank}$). Three new technological routes are also assessed, namely an improved Rankine cycle with condensation turbine ($\mathsf{cond}$), a hydrolysis-based process for 2G ethanol production from bagasse ($\mathsf{hydro}$), and a digester for biogas production from vinasse ($\mathsf{biog}$). Saleable products from the sugarcane plant comprise sugar ($\mathsf{sug}$), ethanol from sugarcane juice and bagasse hydrolysis ($\mathsf{eth}$), fertilizer from vinasse residue ($\mathsf{fert}$), as well as electrical power for either the free market ($\mathsf{free}$) or the regulated market ($\mathsf{reg}$); whereas intermediates or by-products are considered to be sugarcane

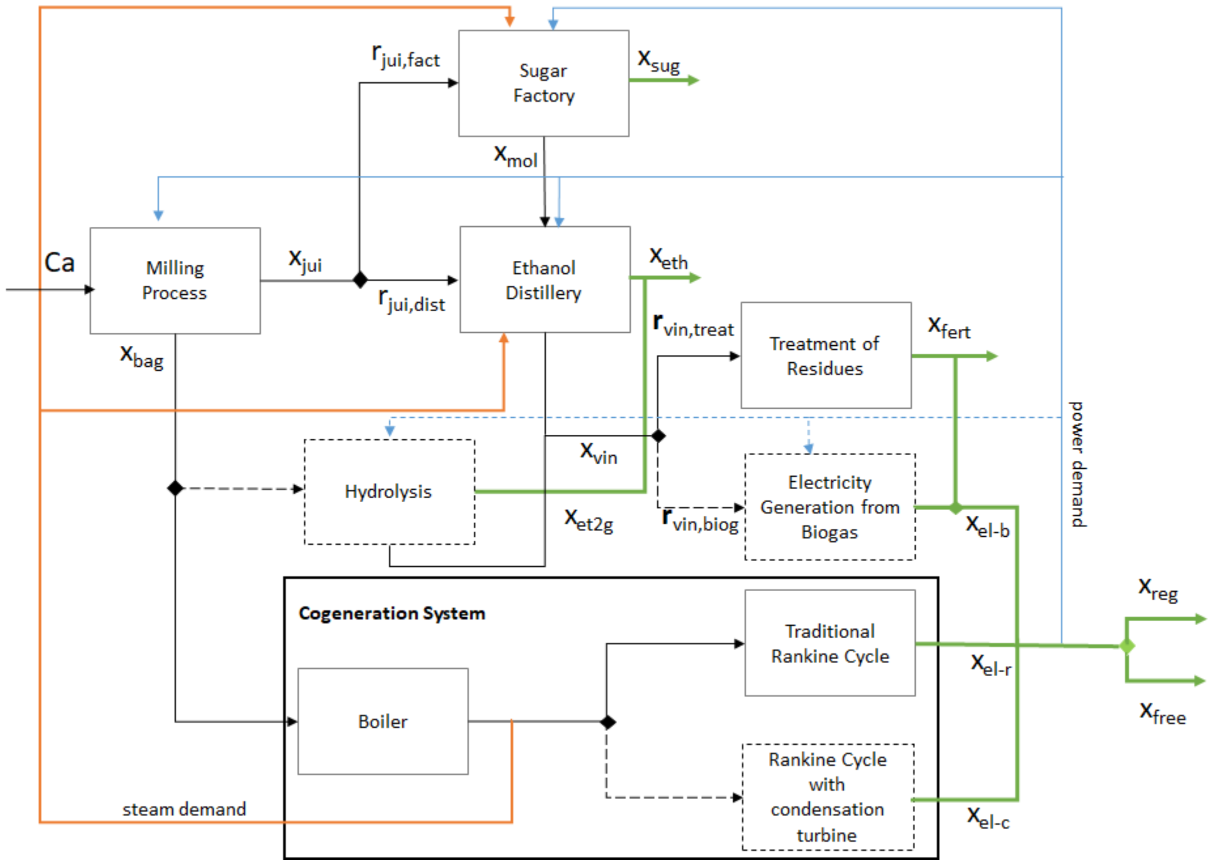


Figure 1: Superstructure of the sugarcane mill process. Each Box represents a process in the sugarcane plant. A solid line indicates the flow of a resource or utility between two or more units. A technological routes subject to investment decision is shown in dotted lines.

(cane), juice (jui), bagasse (bag), molasses (mol), vinasse (vin), 2G ethanol (et2g), and surplus electrical power from the traditional Rankine cycle (el-r), improved Rankine cycle (el-c) and biogas combustion (el-b).

In the mathematical model formulation that follows, the continuous variables $x_i \geq 0$ refer to the yearly production of product $i$; the continuous variables $r_{i,u} \geq 0$ to the yearly amount of product $i$ processed in unit $u$; the discrete (binary or integer) variables $z_u \in \{0, M_u\}$ to the decisions of investing in the new technology $u$ ($z_u \geq 1$) or not ($z_u = 0$), with $M_u \geq 1$ the maximal number of parallel units; the parameters $\theta_{i,u,j}$ to the conversion of product $i$ to product $j$ in unit $u$; the parameters $\gamma_{i,u,j}$ to the yield of product $j$ per unit production of $i$ in unit $u$; and the parameters $\Gamma_u$ to the maximal annual processing capacity of (an existing or prospective) unit $u$.

The sugarcane industrial process starts by squeezing juice out of the sugarcane stalks, which produces bagasse as a residue, and then treating this raw juice into clarified juice. For a given amount of sugarcane to be crushed during the season, Ca, the annual production of juice and bagasse from the sugarcane milling is given by:

$$x_{\mathsf{jui}} = \mathsf{Ca}\ \theta_{\mathsf{cane,mil,jui}} \tag{1}$$

$$x_{\mathsf{bag}} = \mathsf{Ca}\ \theta_{\mathsf{cane,mil,bag}} \tag{2}$$

Notice that the yearly production of juice and bagasse is therefore fixed when both the sugarcane feedstock and the conversion parameter are assumed constant. The first production decision entails sharing the clarified juice between the sugar factory and the ethanol distillery as constrained by the plant's installed capacity:

$$x_{\mathsf{jui}} = r_{\mathsf{jui,fact}} + r_{\mathsf{jui,dist}} \tag{3}$$

$$r_{\mathsf{jui},u} \leq \Gamma_u\ , \quad u \in \{\mathsf{fact}, \mathsf{dist}\} \tag{4}$$

The sugar factory produces sugar crystals and molasses as a by-product:

$$x_{\mathsf{sug}} = r_{\mathsf{jui,fact}}\ \theta_{\mathsf{jui,fact,sug}} \tag{5}$$

$$x_{\mathsf{mol}} = x_{\mathsf{sug}}\ \gamma_{\mathsf{sug,fact,mol}} \tag{6}$$

Integrated sugar and ethanol plants further process molasses in the ethanol distillery alongside the rest of the clarified juice, to produce (hydrous or anhydrous) ethanol and the vinasse by-product:

$$x_{\mathsf{eth}} = r_{\mathsf{jui,dist}}\ \theta_{\mathsf{jui,dist,eth}} + x_{\mathsf{mol}}\ \theta_{\mathsf{mol,dist,eth}} + x_{\mathsf{et2g}} \tag{7}$$

$$x_{\mathsf{vin}} = x_{\mathsf{eth}}\ \gamma_{\mathsf{eth,dist,vin}} \tag{8}$$

The new variable $x_{\mathsf{et2g}}$ in the right-hand side of Eq. (7) represents 2G ethanol production from hydrolysis of bagasse and will be specified later.

A second decision at this stage is whether to use vinasse for fertirrigation of sugarcane plantations, or feed it to an anaerobic digester for biogas production, which in turn is used for surplus electrical power production:

$$x_{\mathsf{vin}} = r_{\mathsf{vin,treat}} + r_{\mathsf{vin,biog}} \tag{9}$$

$$x_{\mathsf{fert}} = r_{\mathsf{vin,treat}}\ \theta_{\mathsf{vin,treat,fert}} \tag{10}$$

$$x_{\mathsf{el\text{-}b}} = r_{\mathsf{vin,biog}}\ \theta_{\mathsf{vin,biog,el\text{-}b}} \tag{11}$$

$$x_{\mathsf{el\text{-}b}} \leq \Gamma_{\mathsf{biog}}\ z_{\mathsf{biog}} \tag{12}$$

Notice that the latter inequality forces the variable $x_{\mathsf{el\text{-}b}}$ to zero in case the decision is made to not invest in a vinasse digester.

Since part of the bagasse is used to cover internal needs in steam and electricity, only surplus bagasse is available for the production of extra saleable products. A third decision therefore entails selecting either one of the following three scenarios (Fig. 1):

- the current scenario, which uses a traditional co-generation system and does not use all of surplus bagasse;
- investment in an improved Rankine cycle with condensation turbine, whereby all of surplus bagasse is used for extra power generation;
- investment in a hydrolysis process, which converts all of surplus bagasse to 2G ethanol.

Mutual-exclusiveness of these scenarios is enforced as:

$$1 = z_{\mathsf{rank}} + z_{\mathsf{cond}} + z_{\mathsf{hydro}} \tag{13}$$

$$x_{\mathsf{el\text{-}r}} \leq \Gamma_{\mathsf{rank}} \left(z_{\mathsf{rank}} + z_{\mathsf{hydro}}\right) \tag{14}$$

$$x_{\mathsf{el\text{-}c}} \leq \Gamma_{\mathsf{cond}}\ z_{\mathsf{cond}} \tag{15}$$

$$x_{\mathsf{et2g}} \leq \Gamma_{\mathsf{hydro}}\ z_{\mathsf{hydro}} \tag{16}$$

And the decision regarding the selling of surplus electrical power to either the free market or the regulated market is given by:

$$x_{\mathsf{reg}} + x_{\mathsf{free}} \leq x_{\mathsf{el\text{-}r}} + x_{\mathsf{el\text{-}c}} + x_{\mathsf{el\text{-}b}} \tag{17}$$

A further complication arises from the need to model the dependency between the yearly amount of surplus bagasse available and the sugar-ethanol production shares. Modelling the steam and power utility streams as part of the process superstructure would provide a way of describing these interdependencies, yet at the cost of increasing the model complexity significantly. Instead our approach entails approximating these dependencies with piecewise linear models that we derive from detailed plantwide simulation of the sugarcane mill of interest—see Sec. 4 for details, and Fig. 4 for an example of surplus electrical power and 2G ethanol from bagasse.

A partition of the sugar-ethanol production share into $L$ subintervals can be created via the following mixed-integer linear constraints:

$$r_{\mathsf{jui,fact}} = \left[\hat{f}^0 + \sum_{k=1}^{L} \left(\hat{f}^k - \hat{f}^{k-1}\right) \xi_k\right] \ \mathsf{Ca}\ \theta_{\mathsf{cane,mil,jui}} \tag{18}$$

$$\xi_k \geq y_k \geq \xi_{k+1}\,, \quad k = 1 \ldots L-1 \tag{19}$$

where $\hat{f}^k$, $k = 0 \ldots L$ are breakpoints representing the fraction of juice sent to the sugar factory in the piecewise linear approximation; $y_k \in \{0, 1\}$, $k = 1 \ldots L-1$ and $\xi_k \in [0, 1]$, $k = 1 \ldots L$ are auxiliary binary and continuous variables, respectively, used to identify the correct subinterval. Then the corresponding productions of electrical power and 2G ethanol are predicted as:

$$x_i \leq \hat{x}_i^0 + \sum_{k=1}^{L} \left(\hat{x}_i^k - \hat{x}_i^{k-1}\right) \xi_k\,, \quad i \in \{\mathsf{el\text{-}r}, \mathsf{el\text{-}c}, \mathsf{et2g}\} \tag{20}$$

where $\hat{x}_i^k$, $k = 0 \ldots L$ denote the predicted yearly production of product $i$ for each juice fraction breakpoint $\hat{f}^k$. Notice that an inequality is used in Eq. (20) as the actual production of $i$ may only be nonzero when the corresponding technology is selected (Eqs. 14–16); instead we rely on the optimizer (Sec. 3.2) for maximizing the production. Overall, the sugarcane plant model (1)–(20) comprises mixed-integer linear equality and inequality constraints.

### 3.2. Portfolio optimization model

The primary objective of the optimization model is to enable risk-conscious decisions in terms of both annual production and investment planning. We assume the market prices of the various saleable products to be the sole source of uncertainty, and we use historical price records to quantify this uncertainty and de-risk the decisions against similar future short-falls. Therefore, the reliability of our results hinges on the assumption that future market conditions will keep following a similar pattern over the optimization horizon. Another key assumption is about the fixed amount of sugarcane, $\mathsf{Ca}$, that is available for crushing during each season. Yearly variations in sugarcane productivity can be as much as 10% due to the local climatic conditions [52] but producers are usually well-aware of the average sugarcane production of their plantations. In committing to the regulated market these producers are further protected by a special clause in their contracts with the government, whereby failure to supply the contracted amount of electricity in a given year can be compensated over a period of four years without incurring a financial penalty [62]. Such averaging over several seasons acts as a de-risking strategy for the sugarcane industry and the main reason why we do not account for the variability in sugarcane production as extra uncertainty in the optimization model.

We consider the conditional-value-at-risk (CVaR) as risk measure in our optimization model, also known as the expected shortfall [24, 63]. The CVaR at a given confidence level $\beta$ corresponds to the expected value of the $100(1-\beta)\%$ worst scenarios. CVaR is an alternative to the value-at-risk (VaR) that is more sensitive to the shape of the tail of the scenario distribution. It is furthermore a coherent [23] and convex measure of risk, which is amenable to a tractable, fully linear formulation in optimization problems [24].

Suppose that $q = 1 \ldots Q$ historical price observations, $\mathsf{HP}_{i,q}$ and production costs, $\mathsf{PC}_i$ are available for each saleable product $i \in \{\mathsf{sug}, \mathsf{eth}, \mathsf{fert}, \mathsf{reg}, \mathsf{free}\}$, alongside equivalent annual costs (EAC), $\mathsf{IC}_u$ for the investment in each prospective technology $u \in \{\mathsf{cond}, \mathsf{hydro}, \mathsf{biog}\}$. For a given process configuration and operation, as represented by the variables $z$ and $x$, the profit corresponding to each price observation is:

$$P_q = \sum_i (\mathsf{HP}_{i,q} - \mathsf{PC}_i) x_i - \sum_u \mathsf{IC}_u z_u, \quad q = 1 \ldots Q$$

The expected profit is readily calculated as:

$$\mathsf{EP} = \frac{1}{Q} \sum_{q=1}^{Q} P_q$$

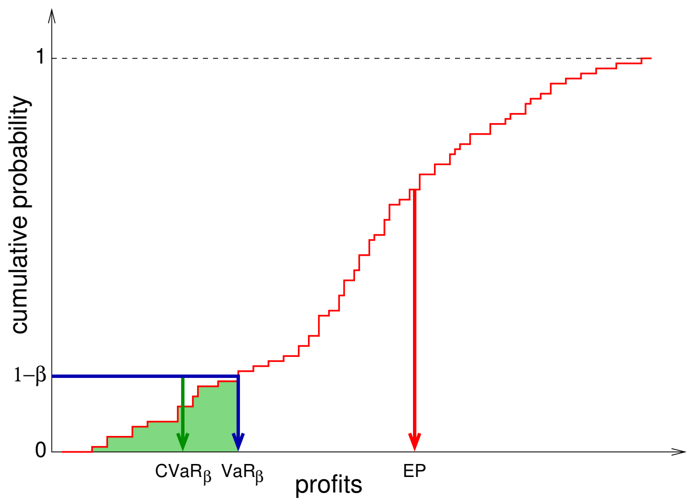


Figure 2: Graphical depiction of the expected profit (EP), value-at-risk (VaR) and conditional-value-at-risk (CVaR) for a sampled profit distribution, in connection with the portfolio optimization model (23).

The VaR at a given confidence level $\beta$ corresponds to the $(1-\beta)$ percentile of the profit distribution (Fig. 2), namely the lowest yearly profit after excluding all worse profits whose combined probability is at most $(1-\beta)$. For the set of sampled profits $P_q$, it is formally defined as:

$$\mathsf{VaR}_\beta = \max_V \ V \ \text{ s.t. } \sum_{q=1}^{Q} \mathbf{1}[V - P_q] \leq (1-\beta)Q \tag{21}$$

where $\mathbf{1}[\cdot]$ stands for the Heavside step function, such that $\mathbf{1}[x] = 1$ for $x \geq 0$ and $\mathbf{1}[x] = 0$ otherwise. The CVaR, in turn, corresponds to the expected value over all profits lower than the VaR (Fig. 2):

$$\mathsf{CVaR}_\beta = \mathsf{VaR}_\beta - \frac{1}{(1-\beta)Q} \sum_{q=1}^{Q} \max\{0, \mathsf{VaR}_\beta - P_q\} \tag{22}$$

It is noteworthy that VaR and CVaR are classically considered loss functions to be minimized in portfolio optimization [24] (right tailed), whereas they are maximized to mitigate risk in the present context (left tailed). Instead of calculating CVaR via Eqs. (21)–(22), which may be cumbersome, Rockafellar and Uryasev [24] established that CVaR can be computed as the maximum value of the following concave function:

$$\Psi(V) = V - \frac{1}{(1-\beta)Q} \sum_{q=1}^{Q} \max\{0, V - P_q\}$$

We use this property in the optimization problem statement below.

Overall, the portfolio optimization model for the sugarcane plant superstructure in Fig. 1 can be stated as:

$$\max_{\substack{x,r,\xi,y,z,\\P,S,V}} \quad \Bigg\{ \underbrace{\frac{1}{Q}\sum_{q=1}^{Q} P_q}_{\mathsf{EP}},\ \underbrace{V - \frac{1}{Q(1-\beta)}\sum_{q=1}^{Q} S_q}_{\mathsf{CVaR}_\beta} \Bigg\} \tag{23}$$

$$\begin{aligned} \text{s.t.}\ \ & \text{Sugarcane plant model (1)–(20)} \\ & \forall q = 1 \dots Q, \\ & \quad P_q = \sum_i (\mathsf{HP}_{i,q} - \mathsf{PC}_i) x_i - \sum_u \mathsf{IC}_u z_u \\ & \quad S_q \geq V - P_q \\ & \quad S_q \geq 0 \end{aligned}$$

where $S_q$ are auxiliary variables representing the possible shortfall in each scenario $q = 1 \dots Q$. The optimization problem (23) is bi-objective, seeking a trade-off between the expected profit $\mathsf{EP}$ and the risk measure $\mathsf{CVaR}_\beta$. The Pareto frontier [64] is defined as the set of all non-dominated points in the sense that no better feasible solution exists in terms of the two objectives simultaneously: betterment of $\mathsf{EP}$ compared to a point on the Pareto frontier results in worsening $\mathsf{CVaR}_\beta$; and vice versa.

We apply the $\epsilon$-constraint method to characterize the Pareto frontier [64]. This method starts by computing the extreme points of the Pareto frontier. Here, we solve the single-objective optimization problems to maximize $\mathsf{EP}$ and $\mathsf{CVaR}_\beta$ separately. In the second step of the $\epsilon$-constraint method a single-objective optimization problem is formulated for one of the objectives, while restraining the possible values taken by the other objectives. We state this single-objective optimization in terms of $\mathsf{CVaR}_\beta$ here:

$$\max_{\substack{x,r,\xi,y,z,\\P,S,V}} \quad V - \frac{1}{Q(1-\beta)}\sum_{q=1}^{Q} S_q \tag{24}$$

$$\begin{aligned} \text{s.t.}\ \ & \text{Sugarcane plant model (1)–(20)} \\ & \frac{1}{Q}\sum_{q=1}^{Q} P_q \geq \overline{\mathsf{EP}} \\ & \forall q = 1 \dots Q, \\ & \quad P_q = \sum_i (\mathsf{HP}_{i,q} - \mathsf{PC}_i) x_i - \sum_u \mathsf{IC}_u z_u \\ & \quad S_q \geq V - P_q \\ & \quad S_q \geq 0 \end{aligned}$$

Then we solve multiple instances of this optimization problem by varying the parameter $\overline{\mathsf{EP}}$ within the extreme points $[\mathsf{EP}^{\min}, \mathsf{EP}^{\max}]$ of the Pareto frontier. These optimization problems fall into the class of mixed-integer linear programming (MILP). Our implementation uses the optimization platform GAMS, from which we call the MILP solver CPLEX. We make our GAMS code available in the Supplementary Material.

## 4. Results and discussion

Our case study features a sugarcane plant processing 3 million tons of sugarcane per year ($\mathsf{Ca}$), which is an average-size facility in Brazil. This plant produces a mix of sugar and ethanol in an integrated production system, as per the superstructure shown in Fig. 1. Its cogeneration system is a traditional Rankine cycle powered by a 67 bar boiler at 520 °C, which generates an average surplus of electricity of 53 kWh for each tonne of sugarcane processed. The addition of a condensation turbine of 40 MW in one investment scenario would increase this surplus of electricity to about 83 kWh per tonne of sugarcane. An alternative investment scenario would retain the existing cogeneration system and integrate a hydrolysis process for 2G ethanol production from surplus bagasse, with a yield of about 0.16 cubic-meter of ethanol for each tonne of bagasse processed (see [6]). Lastly, a complementary investment adds (possibly multiple copies of) an anaerobic digester coupled to an RCE, which would generate a surplus of electricity of about 33 kWh for each cubic-meter of vinasse processed (see [11]).

The investment and production costs ($\mathsf{PC}_i, \mathsf{IC}_u$) reported in Table 1 are from the literature. Each investment cost is reported in terms of an EAC. Since the production cost of prospective technologies may be unknown or unreliable, we assume as a first approximation that the production costs of ethanol and electricity are the same for all the possible technological routes: cost for 1G or 2G ethanol and sugar productions from [65]; and cost of electricity produced by basic or improved cogeneration system or vinasse digester from [37].

Table 1: Investment and production costs relative to the portfolio optimization model (24) (2010 US$)

| **Parameter** | **Value** | **Source** |
|---|---|---|
| $\mathsf{PC}_{\mathsf{sug}}$ | US$322 per tonne of sugar | [65] |
| $\mathsf{PC}_{\mathsf{eth}}$ | US$502 per cubic-meter of ethanol | [65] |
| $\mathsf{PC}_{\mathsf{fert}}$ | US$0.5 per liter of vinasse | [10] |
| $\mathsf{PC}_{\mathsf{free}}$ | US$2 per mega-Watt-hour | [37] |
| $\mathsf{PC}_{\mathsf{reg}}$ | US$2 per mega-Watt-hour | [37] |
| $\mathsf{IC}_{\mathsf{cond}}$ | US$5.5MM per year | [6] |
| $\mathsf{IC}_{\mathsf{hydro}}$ | US$44.4MM per year | [6] |
| $\mathsf{IC}_{\mathsf{biog}}$ | US$1MM per year | [11] |

We consider a confidence level of $\beta = 90\%$ to calculate the risk in the portfolio optimization model (24) throughout. We assume that all of the produced fertilizer is reused for fertirrigation of the sugarcane plantation, not sold to the market ($\mathsf{HC}_{\mathsf{fert},q} = 0$), and that both raw vinasse and digested vinasse have equivalent fertilizing capacity; see Sec. 4.1.2 for further discussions. For the market prices of sugar and ethanol ($\mathsf{HC}_{\mathsf{sug},q}$, $\mathsf{HC}_{\mathsf{eth},q}$), we use weekly price records over the period of 2002–2018 [66, 67]—a total of $Q = 868$ observations, all expressed for the same base-year of 2010 US$ after discounting the effect of inflation (Fig. 3). By contrast, historical prices for electricity in the free market ($\mathsf{HC}_{\mathsf{free},q}$) are not directly available since the transactions are agreed bilaterally over the counter, without public price disclosure, and the contracts are not comparable due to the particularities of each transaction. Instead we use historical PLD prices as proxies for the electricity prices contracted on the free market, in the form of weekly price records over the period of 2002–2018 [68] (Fig. 3). PLD prices have been shown to be correlated with free market prices [62], in particular for the shorter-term contracts, and we note that this approximation has also been used in other recent production-mix optimization studies [38, 69]. Finally, the price of electricity in the regulated market ($\mathsf{HC}_{\mathsf{reg},q}$) is set as a parameter in the scenario analysis below.

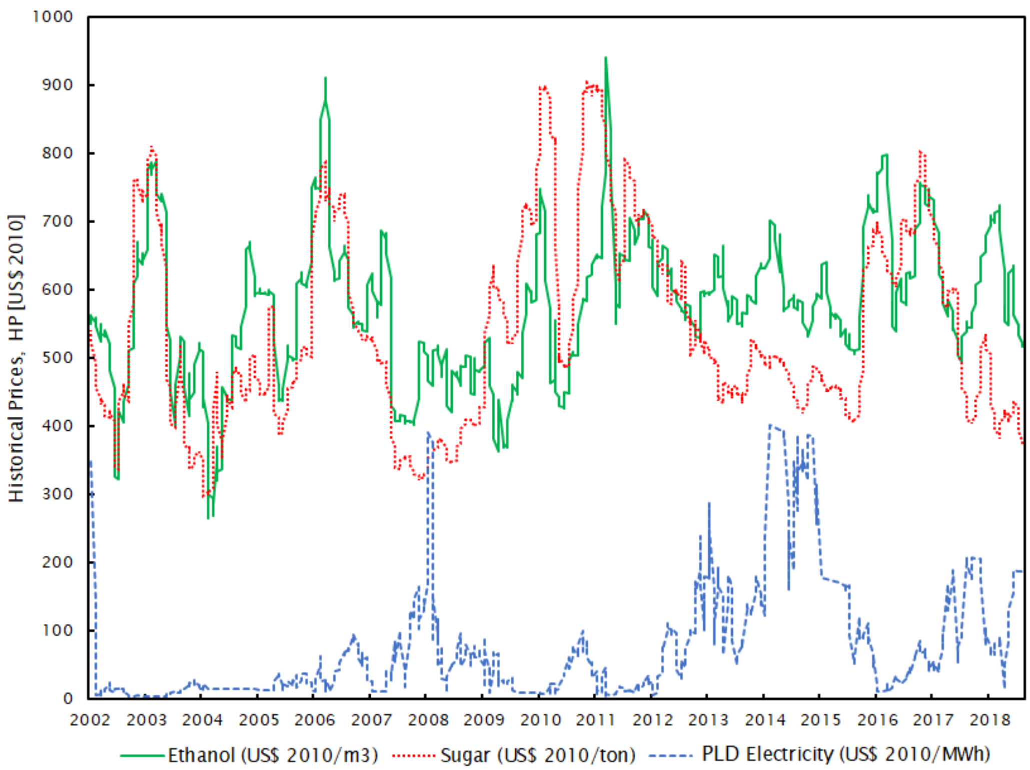


Figure 3: Historical prices of sugar, ethanol and spot electricity (PLD).

The process yields, waste generation rates and internal consumption of steam and power are derived from the Open Sugarcane Process Simulation Platform [36]—the operation conditions and process specifications used for the simulation of the sugarcane plant are summarized in Table 2 for completeness. For instance, the simulator computes the amount of surplus bagasse corresponding to various sugar-ethanol production shares, which is then used to predict the production of surplus electricity ($x_{\mathsf{el\text{-}r}}, x_{\mathsf{el\text{-}c}}$) and 2G ethanol ($x_{\mathsf{et2g}}$) in the different investment scenarios—these variations are shown in Fig. 4. Two plantwide models are compared hereafter, the first one adopting a piecewise-linear representation of the variations (Eq. 18–20) and the second using an average value. The other parameters in the plantwide model (Eq. 1–20) are specified in Table 3.

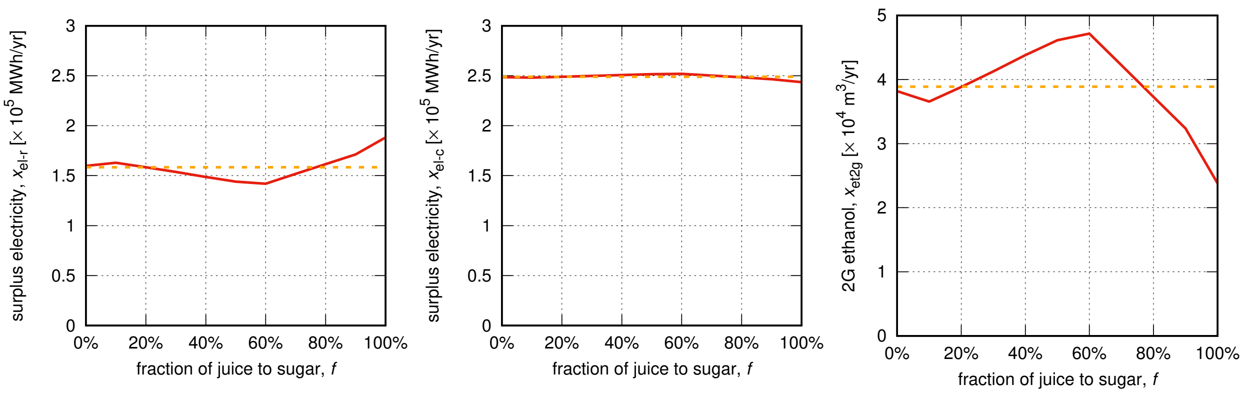


Figure 4: Effect of the sugar-ethanol production share ($f$) on the production of: surplus electricity from the traditional Rankine cycle ($x_{\text{el-r}}$, left plot); surplus electricity from the improved Rankine cycle ($x_{\text{el-c}}$, middle plot); and 2G ethanol from the hydrolysis of surplus bagasse ($x_{\text{et2g}}$, right plot). Solid line: simulation using the Open Sugarcane Process Simulation Platform [36]. Dashed line: average value.

Table 2: Operating parameters used in the Open Sugarcane Process Simulation Platform [36].

| **Parameter** | **Value** |
|---|---|
| Fibre % Cane | 13.0% |
| Sucrose wt% | 15.0% |
| Bagasse | 26.6% |
| Extraction efficiency | 97.7% |
| Boiler steam pressure | 67 bar |
| Boiler temperature | 520 °C |
| Boiler efficiency | 79% |
| Back pressure turbine efficiency | 82% |
| Condensation turbine efficiency | 73% |

Our analysis in the following subsections relies on the solution of various instances of the portfolio optimization model (Eq. 24), aiming to compare different modeling assumptions (Sec. 4.1.1) as well as analyzing the sensitivity of investment decisions (Sec. 4.1.2), product-mix decisions (Sec. 4.2), and market prices and governmental policies (Sec. 4.3).

### *4.1. Base scenario*

The electricity price in the regulated market is set to be US$72.50/MWh in our base scenario, which is representative of the average auction price practiced over the period 2011–2014 (for new bioenergy generation

Table 3: Parameter values in the plantwide model (1)–(20), derived from the Open Sugarcane Process Simulation Platform [36].

| **Parameter** | **Value** | **Units** |
|---|---|---|
| $\Gamma_{\mathsf{rank}}$ | 200,000 | mega-Watt-hour per year |
| $\Gamma_{\mathsf{cond}}$ | 300,000 | mega-Watt-hour per year |
| $\Gamma_{\mathsf{hydro}}$ | 41,000 | cubic-meter of ethanol per year |
| $\Gamma_{\mathsf{biog}}$ | 26,000 | mega-Watt-hour per year |
| $\gamma_{\mathsf{sug,fact,mol}}$ | 1.05 | tonne of molasses per tonne of sugar |
| $\gamma_{\mathsf{eth,dist,vin}}$ | 10.0 | cubic-meter of vinasse per cubic-meter of ethanol |
| $\theta_{\mathsf{cane,mill,jui}}$ | 0.734 | tonne of juice per tonne of sugarcane |
| $\theta_{\mathsf{cane,mill,bag}}$ | 0.266 | tonne of bagasse per tonne of sugarcane |
| $\theta_{\mathsf{jui,fact,sug}}$ | 0.123 | tonne of sugar per tonne of juice |
| $\theta_{\mathsf{jui,dist,eth}}$ | 0.123 | cubic-meter of ethanol per tonne of juice |
| $\theta_{\mathsf{mol,dist,eth}}$ | 0.375 | cubic-meter of ethanol per tonne of molasse |
| $\theta_{\mathsf{vin,treat,fert}}$ | 1.0 | cubic-meter of fertilizer per cubic-meter of vinasse |
| $\theta_{\mathsf{vin,\ biog,\ el\text{-}b}}$ | 0.0329 | mega-Watt-hour per cubic-meter of vinasse |

capacity to be installed by the end of 2019). We furthermore consider the optimistic scenario whereby the mix of sugar and ethanol is entirely flexible between 0–100% throughout this subsection.

#### *4.1.1. Effect of modeling assumptions*

A simplifying assumption made by portfolio optimization studies in the sugarcane sector to date [10, 38, 39] is that the yearly amount of surplus bagasse is independent of the share of sugar and ethanol (see literature review, Sec. 2.2). We address this shortcoming by taking these interdependencies into account for optimal product-mix decisions. A comparison between the solutions of the portfolio optimization model (24) with either piecewise-linear (**base**) or constant (**fixed rate**) profiles of surplus electricity and 2G ethanol is presented in Fig. 5.

Recall that in our portfolio optimization formulation a greater CVaR entails a lower risk. Therefore, risk-neutral scenarios on the main plot correspond to the left part of the Pareto frontier with the greatest expected profits, while risk-averse scenarios correspond to the right part. The maximal expected profit is high—in the order of US$80MM/yr. But the corresponding CVaR predicts that the expected profit in the 10% worst scenarios could be as low as US$4–14MM/yr, even when a risk-averse strategy is adopted. In other words, the potential for risk mitigation is rather low in this base scenario, which is attributed to a highly volatile market for sugar, ethanol and electricity.

To further this analysis Fig. 6 presents a comparison between the optimal profit distributions under risk-neutral (maximal EP) and risk-averse (maximal CVaR) strategies in the **base** case. The left tail in the risk-averse profit distribution is clearly shorter than in the risk-neutral one while the right tail is longer, but these differences are nonetheless small. The downside of this risk mitigation strategy can be seen in the

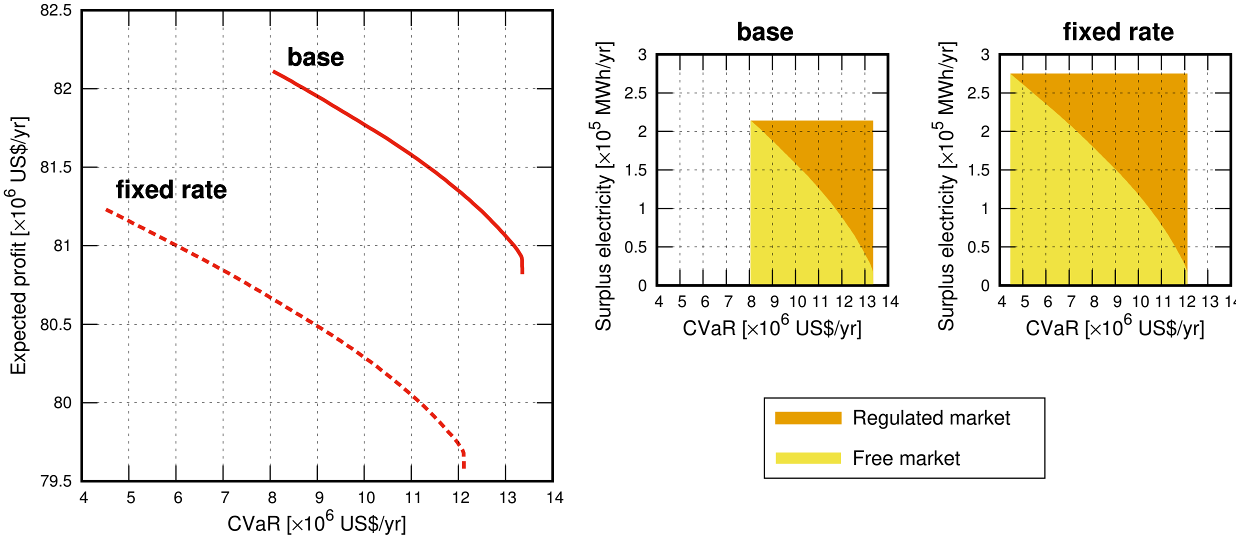


Figure 5: Comparison between optimal portfolio solutions with either piecewise-linear (**base**) or constant (**fixed rate**) profiles of surplus electricity. Main plot (left): Pareto frontier of expected profit versus risk. Secondary plots (right): share of surplus electricity between free and regulated markets under each modeling assumption.

middle part of the distributions, with much higher frequencies in the range between US\$40–80MM/yr under the risk-averse strategy, compared to the risk-neutral strategy where the frequencies are higher in the range between US\$80–140MM/yr and the expected profit is therefore larger.

Notice the large discrepancy between profiles computed with the piecewise-linear and constant approximations on the main plot of Fig. 5, showing differences greater than US\$1MM/yr in expected profit. It is also noteworthy that optimal risk-averse strategies under the piecewise-linear model present a similar expected profit to their risk-neutral counterparts under the constant approximation. Another key difference between both models is notable in terms of investment strategy: the portfolio model with the constant approximation (**fixed rate**) recommends investing in an improved Rankine cycle with condensation turbine ($z_{\mathrm{cond}} = 1$); whereas the piecewise-linear model (**base**) advises against this investment (see the two secondary plots on Fig. 5). On the other hand, the two models present a similar strategy for the sale of surplus electricity between the free and regulated markets, favoring the regulated market for risk mitigation.

Since all of the sugarcane juice is directed to the sugar factory due to an unfavorable ethanol market ($f = 100\%$), the surplus electricity from the traditional Rankine cycle is indeed underestimated by some 20% with the constant approximation, while at the same time the surplus electricity from the improved Rankine cycle is slightly overestimated (see Fig. 4). In fact, this comparison is a clear illustration of how sensitive the decision-making can be to the process models. In the rest of this paper we shall retain the piecewise-linear model, which enables a better description of the interdependencies between decisions and variables in the sugarcane plant.

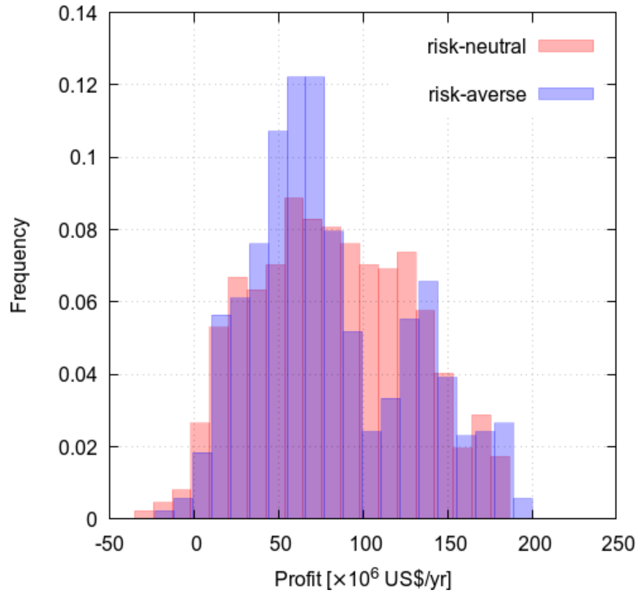


Figure 6: Comparison between optimal profit distributions under risk-neutral and risk-averse strategies in the **base** case.

*4.1.2. Sensitivity of investment decisions*

We have already observed with the piecewise-linear model of surplus bagasse that the addition of a condensation turbine to the existing co-generation is not advisable, regardless of the risk level (CVaR). To assess the distance to Pareto optimality, consider for instance that this investment would become profitable if the turbine cost ($\mathsf{IC}_{\mathsf{cond}}$) were to decrease by US\$1.6MM/yr, a significant reduction of about 30%. The impact of regulated electricity prices on this investment decision will be further discussed in Sec. 4.3.2.

Another key insight from our base scenario is that the investment in a hydrolysis process to produce 2G ethanol from surplus bagasse may not be economically viable by a very large margin. For comparison, the maximal expected profit in a risk-neutral setting is predicted to decrease to below US\$40MM/yr in case this investment was made, a 50% downfall with respect to the best portfolio solutions. The contributing factors are two-fold: the investment cost of the hydrolysis process is high relative to a traditional or improved co-generation system; and due to an unfavorable ethanol market (see further discussion in Sec. 4.3.1) selling ethanol could lead to large financial losses in the worst-case scenarios (negative CVaR). The unfavorable ethanol market was already reflected in the fact that 100% of the sugarcane juice is sent to the sugar factory, while only producing 1G ethanol from molasses.

By contrast, the portfolio model advises to invest in extra electricity generation capacity via the anaerobic digestion of vinasse—a single digester unit is selected here ($z_{\mathsf{biog}} = 1$). A comparison between the solutions of the portfolio optimization model (24) with (**base**) and without (**no biogas**) such an investment is presented in Fig. 7. Electricity generation through biogas combustion leads to a noticeable gain in expected profit, around

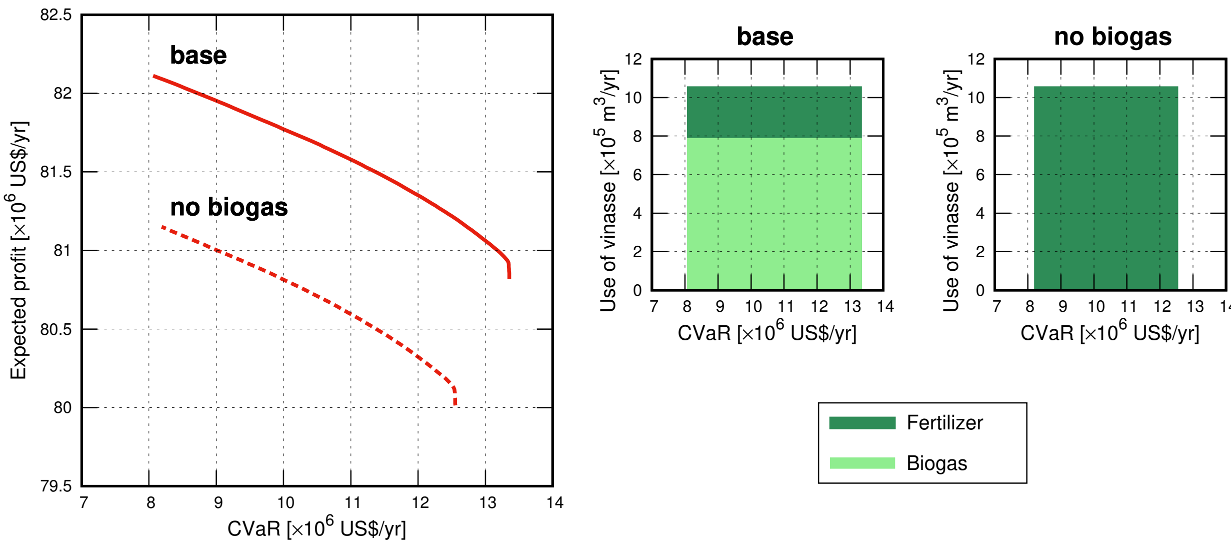


Figure 7: Comparison between optimal portfolio solutions with (**base**) or without (**no biogas**) investment on biogas generation from vinasse. Main plot (left): Pareto frontier of expected profit versus risk. Secondary plots (right): share of vinasse between fertilization and digestion under each scenario.

US$1MM/yr. The financial shortfall corresponding to the risk-averse solutions is furthermore reduced by close to US$1MM/yr. Though still incipient in the sugarcane sector investment in new biogas capacity is predicted to have a very short payback period in our base scenario, which corroborates other studies in the literature [11, 12].

Recall, however, that our base scenario relies on the assumption that all of the digested vinasse can be used in fertirrigation of the sugarcane plantation and therefore the use of anaerobic digestion does not require purchasing extra fertilizer to supplement the fertirrigation. To assess the sensitivity of this assumption we can estimate the price of buying fertilizer instead of fertirrigation, e.g. considering that 300 m$^3$ of vinasse is equivalent to 180 kg of commercial fertilizer [11] as a first approximation. Even in this extreme (and unlikely) scenario, the portfolio model still recommends the investment in an anaerobic digester under both risk-neutral and risk-averse strategies, so long as the price of fertilizer is lower than US$2,000 per tonne—a price 4-time larger than the average price of potash over the last decade [70].

### *4.2. Effect of sugar-ethanol capacity constraints*

The base scenario in Sec. 4.1 assumed a fully flexible mix of sugar and ethanol between 0–100%. This is not representative of the majority of the sugarcane plants in Brazil, where the installed capacity for sugar production varies between 50-75% of the total juice extracted during one season [35]. Because of the unfavorable ethanol market the model in the base scenario advised that all of the sugarcane juice should be processed in the sugar factory, while producing 1G ethanol from the molasses only.

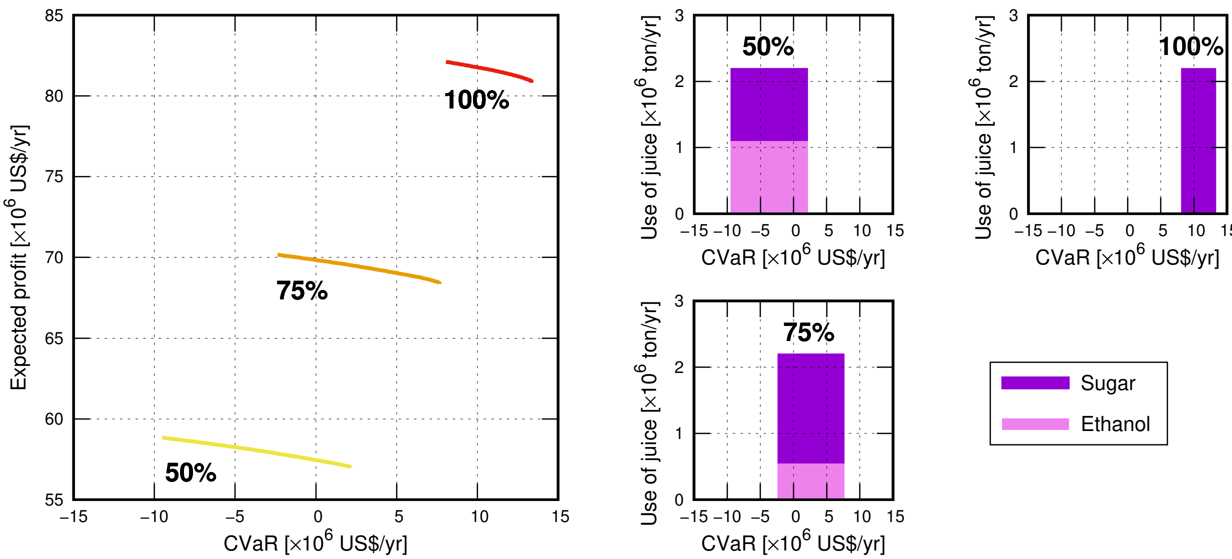


Figure 8: Comparison between optimal portfolio solutions with different capacity constraints on the amount of juice processed by the sugar factory: **50%**, **75%** or **100%** (**base**) of the total juice extracted during one season. Main plot (left): Pareto frontier of expected profit versus risk. Secondary plots (right): share of juice between sugar factory and ethanol distillery under each scenario.

A comparison is made in Fig. 8 between portfolio optimal solution, whereby the capacity parameter $\Gamma_{\mathsf{fact}}$ is adjusted so that a maximum of **50%**, **75%** or **100%** of the total juice is processed in the sugar factory. It is clear from the main plot that the fully flexible process (**100%**) is considerably more profitable than those with capacity restrictions (**50%**, **75%**). The risk of financial shortfall is furthermore significantly higher in these latter scenarios compared to the base case. In the **50%** scenario for instance, the expected profit in the 10% worst scenarios is close to −US\$10MM/yr (loss) under a risk-neutral strategy, and still close to zero under a risk-averse strategy. This analysis suggests that those Brazilian sugarcane mills subject to capacity constraints are indeed at risk of severe financial shortfall, based on the historical market conditions.

Another insight drawn from the model is that upgrading the cogeneration system with a condensation turbine might only be advisable when the capacity constraint on sugar production is below 85% of the total juice extracted. This demonstrates that surplus electricity generation could indeed be used as a hedging strategy for ethanol prices, especially in those mills where capacity constraints do not allow an increase in sugar production for risk mitigation.

### *4.3. Effect of market and governmental policies*

The portfolio optimization clearly supports a production focused on the sugar business. We saw in Sec. 4.2 that the expected profit increases and risk decreases with a higher sugar production capacity. However, this strategy is detrimental to the objective of increasing renewables in the national energy matrix. Instead it is in the best interest of the Brazilian government to implement policies that incentivize ethanol and bioelectricity generation. Several such policies are analyzed in the rest of this subsection.

### *4.3.1. Ethanol market*

The Brazilian government has recently introduced RenovaBio, a national policy aiming to increase the use of all biofuels including ethanol, in order to improve energy security and reduce GHG emissions. Under RenovaBio, the demand in hydrous ethanol is expected to rise from 15.2MM $m^3$ in 2018 to 36MM $m^3$ by 2028, with projected investments of about US$15Bn in ethanol supply, including expansion of existing biorefineries, installation of new sugarcane and corn facilities, and investment in 2G ethanol production [2].

But according to the results obtained in Secs. 4.1 and 4.2, ethanol prices practiced in the Brazilian market have been unfavorable to a production focused on biofuel generation. Next, we assess the impact of a rise in the ethanol prices on the profit of the sugarcane mill and the investment strategy. The investigated scenario imposes a capacity constraint of 70% on the amount of juice processed by the sugar factory, an average for Brazilian sugarcane mills, and sets the electricity price in the regulated market to US$72.50/MWh as in the base scenario (Sec. 4.1).

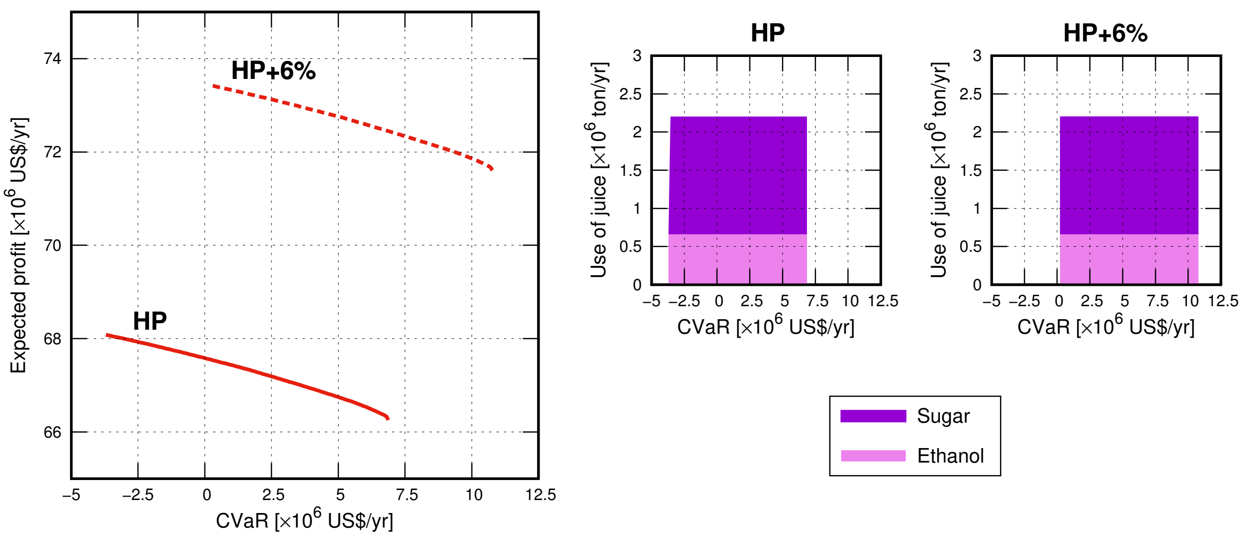


Figure 9: Comparison between optimal portfolio solutions with ethanol prices based on historical records (**HP**) or a rise of historical records by 6% (**HP+6%**). Main plot (left): Pareto frontier of expected profit versus risk. Secondary plots (right): share of juice between sugar factory and ethanol distillery under each scenario.

The comparison presented in Fig. 9 is between portfolio optimal solutions computed from historical records of ethanol prices (**HP**) and the hypothetical scenario of a 6% rise in ethanol prices (**HP+6%**). Albeit small, this rise would be sufficient to mitigate the risk of financial shortfalls even in a risk-neutral strategy. The corresponding increase by about 8% in the expected profit demonstrates how dependent and sensitive the profitability of a sugarcane mill can be to the ethanol business. Such high sensitivity is attributed to the fact that the production cost and market price of ethanol are close to one another in our case study. However, a mere 6% rise in market price of is not sufficient to incentivize 1G ethanol production, as the plant still operates at maximum sugar production capacity in this scenario (see secondary plots on Fig. 9). For the production of 1G ethanol to become profitable over sugar a 30% increase in the historical prices of ethanol would be necessary. This seems highly unlikely in the near future, insofar as ethanol needs to remain (at least) 30% cheaper than gasoline for economic competitiveness in Brazil [3]. Finally, our model advises against investment in 2G ethanol technology from surplus bagasse in all of the ethanol price scenario considered. Despite this route being discussed in the literature for over a decade, its economic feasibility appears to be hindered by the very high investment costs.

#### *4.3.2. Regulated Electricity Market*

The current share of biomass in the Brazilian electricity matrix is close to 9% [71], but it could decrease in the near future due to the recent drop in new bioelectricity projects. Contributing to this disaffection are the high investment costs involved, lack of financing alternatives, and lack of effective pricing policies in biomass auctions [72].

In order to analyze the role played by these auctions we conduct a scenario analysis by varying the prices practiced in the regulated electricity market. For consistency with Sec. 4.3.1 we consider a scenario whereby no more than 70% of the total juice can be processed by the sugar factory. Fig. 10 compares four optimal portfolio solutions corresponding to regulated electricity prices between US$50–80/MWh, where several operational and investment strategies may be distinguished. Since the regulated electricity prices are fixed, and thus essentially risk-free, a producer should always sell to the regulated market when the negotiated electricity price is greater than the expected price in the free market—about US$78/MWh in our case study. This strategy is illustrated by the scenario **80** here.

The three frontiers for which regulated market prices are lower than the expected price in the free market (scenarios **50**–**70**) all originate from the same point, where a risk-inclined producer would sell all of its surplus electricity to the free market. Then risk mitigation entails increasing the share of regulated electricity, which comes at the cost of reducing the expected profit. Notice that for a regulated electricity price of US$50/MWh, the Pareto frontier presents a discontinuity: the decision to invest in a condensation turbine to upgrade the cogeneration system would be made by a risk-inclined producer but not by a risk-averse producer, who could no longer benefit from the safety net offered by a high enough regulated electricity price. By contrast, regulated prices of US$60/MWh and higher are sufficiently attractive to support the investment in a condensation turbine at any risk level and therefore the corresponding Pareto frontiers are continuous.

Overall, an increase in the regulated electricity price gives a much superior range of options to sugarcane

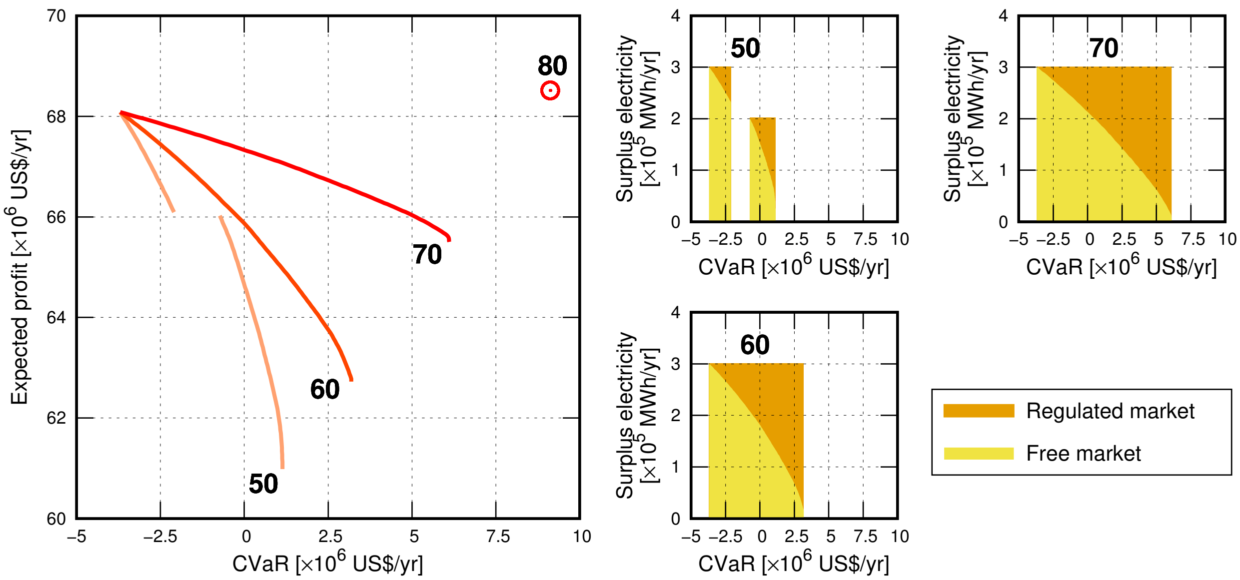


Figure 10: Comparison between optimal portfolio solutions with electricity prices in the regulated market between US$50-80/MWh. Main plot (left): Pareto frontier of expected profit versus risk. Secondary plots (right): share of surplus electricity between free and regulated markets under each scenario.

producers, between risk-neutral and risk-averse strategies. For instance, in the scenario of a regulated electricity price of US$70/MWh the CVaR could be increased by nearly US$10MM/yr. The likelihood of experiencing a shortfall would be significantly reduced by sacrificing just over US$2MM/yr in expected profit. This is an illustration of how long-term electricity contracts could help de-risk other products and investments in the sugarcane business, provided they are priced adequately.

The results of our case study suggest that a price range above US$60-70/MWh might producers' interest in upgrading their cogeneration system in order to generate surplus electricity. With a regulated electricity price around US$50/MWh by contrast, only a risk-inclined producer would choose to invest in new bioelectricty projects, selling most of the surplus electricity to the free market in order to pay back. These results corroborate two auctions performed by the Brazilian government in 2011 with average prices of US$52/MWh and US$57/MWh, which led to significantly less contracted energy than two subsequent auctions in 2013 with average prices of US$65/MWh and US$68/MWh [73]. Naturally there are other market aspects that may influence a producer's willingness to invest, such as economic or political uncertainty in Brazil. But by better understanding the impact of long-term energy contracts on de-risking the sugarcane business, in particular by proposing attractive prices for the energy auctions, policy-makers are more likely to succeed in increasing the share of bioelectricity in the national mix.

## 5. Conclusions

This paper has presented a risk-conscious optimization model to assist product-mix and investment decisions in the Brazilian sugarcane sector. Our methodology combines superstructure process modeling with portfolio optimization in order to enable risk-conscious and faithful solutions despite the complexity of the sugarcane process and volatility of the sugar, ethanol and spot electricity markets. Unlike previous studies our model accounts for the interdependencies between the share of sugar and ethanol and the yearly amounts of surplus bagasse and vinasse, using piecewise-linear relationships derived from a detailed process simulator. In particular, we have established that failure to account for such interdependencies could lead to significant differences in the predicted profits and risks; and could even modify the investment recommendations.

The potential of our portfolio optimization model has been illustrated through the case study of an existing sugarcane mill, where three prospective technological routes were considered for investment. We conducted a detailed scenario analysis to assess the sensitivity of investment decisions, product-mix decisions and market prices, as well as government policies to incentivize bioenergy production from sugarcane by-products and wastes. In all of the scenarios considered the portfolio model recommended investing in extra electricity generation capacity via the anaerobic digestion of vinasse, which benefits from a very short payback period. But it advised against investment in 2G ethanol generation from surplus bagasse, mainly due to the high investment cost of the hydrolysis process, and the consistently low historical price of ethanol. The model also indicated that investment to upgrade the co-generation system with a condensation turbine is highly sensitive to capacity constraints on the sugar-ethanol mix, the regulated electricity price, and the accepted level of risk, all together.

Most of the scenarios confirmed that risk-inclined decisions could lead to severe shortfalls when the market is unfavorable. But adopting a risk-averse strategy could greatly mitigate the risk of shortfall, without sacrificing too much of the expected profit in many scenarios. In the current Brazilian context a risk-averse producer would invest in a vinasse digester and a condensation turbine to increase bioelectricity production if the regulated electricity price were upwards of US$60/MWh, and would sell most surplus electricity to the regulated market as a safety net. Given the unfavorable ethanol market, that producer would also operate the sugarcane plant at its maximum sugar production capacity, while only producing 1G ethanol from molasses. Incentivizing biofuel production in the sugarcane sector appears to be much more challenging though. Albeit raising the ethanol price could have a greater impact on a plant's expected profit than a higher regulated electricity price, this would not be sufficient to interest producers in increasing their 1G ethanol production; let alone the production of 2G ethanol from bagasse, which is still a long way from economic feasibility.

It is important to recall that our case study results rely on the assumption that PLD prices reflect the electricity prices practiced on the free market, at least for short-term contracts. This is not a limitation of the portfolio model per se, but a consequence of the bilateral price agreements in the free market not being disclosed to the public. We expect policy-makers to be able to apply the proposed portfolio optimization model in the same manner, yet with more accurate historical data about the free electrical market.

A relevant follow-up to our work could consider the inclusion of environmental and social aspects in the decision-making model; for instance, in the form of a carbon tax and the social cost of carbon [74, 75]. A more policy-oriented study could also analyze additional criteria, other than financial returns, used by producers to make investment decisions related to bioenergy projects. Another interesting extension to our model could consider sugarcane straw alongside bagasse and vinasse for surplus energy production. Finally, this work has been conducted at the single-plant level, and a natural continuation entails the optimization of a group of sugarcane mills, with a view to exchanging surplus bagasse and accessing larger infrastructure.

## Acknowledgements

Financial support by FAPESP-NERC under grant 2015/50684-9 and FAPESP under grants 2017/17530-3 and 2018/08255-1 is gratefully acknowledged. VM Mutran thanks São Paulo Research Foundation (FAPESP) for student scholarship and Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) for student grant. CAO Nascimento and CO Ribeiro thank Brazilian National Research Council (CNPq) for financial support under grants 306734/2014-1 and 307126/2018-8. The authors are grateful to the editors and the anonymous reviewers for their thoughtful comments that led to substantial improvement of the article. Finally, special thanks go to Mrs Jessica Monteith-Chachuat for her careful proofreading of the paper and useful suggestions.

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## Nomenclature

### Acronyms

1G first generation

2G second generation

CHP combined heat and power

CVaR conditional-value-at-risk

EAC equivalent annual cost

EP expected profit

GHG greenhouse gas

MILP mixed-integer linear programming

NDC nationally determined contributions

PSE process systems engineering

RCE reciprocating combustion engine

VaR value-at-risk

### Main Symbols

$\beta$ confidence level

$\gamma_{i,u,j}$ yield of product $j$ per unit production of $i$ in unit $u$

$\Gamma_u$ maximal annual processing capacity of unit $u$

$\hat{f}^k$ breakpoint for juice fraction share in piecewise linear formulation

$\hat{x}_i^k$ predicted yearly production of product $i$ corresponding to breakpoint $\hat{f}^k$

$\mathsf{Ca}$ yearly amount of sugarcane crushed

$\theta_{i,u,j}$ conversion of product $i$ to product $j$ in unit $u$

$\xi_k$ auxiliary continuous variable in piecewise linear representation

$L$ number of breakpoints in piecewise linear representation

$M_u$ maximal number of parallel units $u$

$P_q$ profit corresponding to price observation $q$

$Q$ number of historical price observations

$r_{i,u}$ yearly amount of product $i$ processed in unit $u$

$S_q$ shortfall corresponding to price observation $q$

$V$ auxiliary continuous variable in CVaR formulation

$x_i$ yearly production of product $i$

$y_k$ auxiliary binary variable in piecewise linear representation

$z_u$ decision to invest in the technology $u$

$\mathsf{HP}_{i,q}$ price observation $q$ for saleable product $i$

$\mathsf{IC}_u$ EAC for investment in technology $u$

$\mathsf{PC}_i$ production cost of saleable product $i$

### Subscripts

bag bagasse

biog digester for biogas production from vinasse

cane sugarcane stalks

cond improved Rankine cycle with condensation turbine

dist ethanol distillery

et2g second-generation ethanol

eth ethanol from sugarcane juice and bagasse hydrolysis

fact sugar factory

fert fertilizer from vinasse residue

free free market electricity

hydro hydrolysis-based process for 2G ethanol production from bagasse

jui sugarcane juice

mill sugarcane milling

mol molasses

rank traditional Rankine cycle with back-pressure turbine

reg regulated market electricity

sug sugar crystals

treat treatment of vinasse residues

vin vinasse

el-b surplus electricity from biogas combustion

el-c surplus electricity from improved Rankine cycle

el-r surplus electricity from traditional Rankine cycle