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# Design and planning of infrastructures for bioethanol and sugar production under demand uncertainty

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ABSTRACT

In this paper, we address the strategic planning of integrated bioethanol–sugar supply chains (SC) under uncertainty in the demand. The design task is formulated as a multi-scenario mixed-integer linear programming (MILP) problem that decides on the capacity expansions of the production and storage facilities of the network over time along with the associated planning decisions (i.e., production rates, sales, etc.). The MILP model seeks to optimize the expected performance of the SC under several financial risk mitigation options. This consideration gives a rise to a multi-objective formulation, whose solution is given by a set of network designs that respond in different ways to the actual realization of the demand (the uncertain parameter). The capabilities of our approach are demonstrated through a case study based on the Argentinean sugarcane industry. Results include the investment strategy for the optimal SC configuration along with an analysis of the effect of demand uncertainty on the economic performance of several biofuels SC structures.



*Keywords:* Supply chain optimization; Planning; Bioethanol supply chain; Sugar supply chain; Financial risk management; Stochastic programming

## 1. Introduction

Ethanol is nowadays regarded as a successful example of a global shift away from fossil sources of energy to bio-based fuels. The use of ethanol as a transport fuel began in the 1970s, and was motivated by the oil crisis and the need to develop alternative fuel programs for reducing the dependence on oil. Among the various alternative fuels, ethanol is one of the most suitable ones for spark-ignition engines. It is produced from renewable sources and does not contain the impurities present in petroleum-derived products, such as sulphur compounds and carcinogenic aromatics, which are the main sources of pollution in large metropolitan areas. Ethanol and ethanol–gasoline blends have several advantages over conventional gasoline such as the reduction of fossil-originated $CO_2$ emissions, better anti-knock characteristics, and higher power output and fuel economy (Hsieh et al., 2002). Moreover, the higher auto-ignition temperature and flash point of ethanol lead to lower evaporation loses (Niven, 2005). The use of ethanol has also some disadvantages such as the increase of $NO_x$ and noise emissions (Bayraktar, 2005; Keshkin, 2010). In addition, the gasoline blends with ethanol have a tendency to absorb water and therefore require special storage conditions to prevent a degradation of fuel properties (Muzikova et al., 2009).

Fuel ethanol was firstly adopted by Henry Ford in 1896. The large-scale production of ethanol for the transportation sector, however, did not begin until the late 1970s, and took place mainly in Brazil and US. In 1975, Brazil launched the national alcohol program *Pró-álcool* sponsoring the development of ethanol-fueled cars. By 1986, 72.6% of light vehicles sold in Brazil operated exclusively with pure ethanol (ANFAVEA,

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## Nomenclature

*Indices*

| | |
|---|---|
| $e$ | scenario |
| $i$ | material |
| $g$ | sub-region |
| $k$ | target value |
| $l$ | transportation mode |
| $p$ | manufacturing technology |
| $s$ | storage technology |
| $t$ | time period |

*Sets*

| | |
|---|---|
| $IL(l)$ | set of materials that can be transported via transportation mode $l$ |
| $IM(p)$ | set of main products for each technology $p$ |
| $IS(s)$ | set of materials that can be stored via storage technology $s$ |
| $SEP$ | set of products that can be sold |
| $SI(i)$ | set of storage technologies that can store materials $i$ |

*Parameters*

| | |
|---|---|
| $\alpha^{PL}_{p,g,t}$ | fixed investment coefficient for technology $p$ |
| $\alpha^{S}_{s,g,t}$ | fixed investment coefficient for storage technology $s$ |
| $\beta$ | storage period |
| $\beta^{PL}_{p,g,t}$ | variable investment coefficient for technology $p$ |
| $\beta^{S}_{s,g,t}$ | variable investment coefficient for storage technology $s$ |
| $\rho_{p,i}$ | material balance coefficient associated with material $i$ and technology $p$ |
| $\tau$ | minimum desired percentage of the available installed capacity |
| $\varphi$ | tax rate |
| $avl_l$ | availability of transportation mode $l$ |
| $CapCrop_{g,t}$ | total capacity of sugar cane plantations in sub-region $g$ in time $t$ |
| $DW_{l,t}$ | driver wage |
| $EL_{g,g'}$ | distance between $g$ and $g'$ |
| $\overline{FCI}$ | upper limit on the capital investment |
| $FE_l$ | fuel consumption of transport mode $l$ |
| $FP_{l,t}$ | fuel price |
| $GE_{l,t}$ | general expenses of transportation mode $l$ |
| $LT_{i,g}$ | landfill tax |
| $ME_l$ | maintenance expenses of transportation mode $l$ |
| $\overline{PCap_p}$ | maximum capacity of technology $p$ |
| $\underline{PCap_p}$ | minimum capacity of technology $p$ |
| $\overline{PR_{i,g,t}}$ | prices of final products |
| $\overline{Q_l}$ | maximum capacity of transportation mode $l$ |
| $\underline{Q_l}$ | minimum capacity of transportation mode $l$ |
| $\overline{SCap_s}$ | maximum capacity of technology $p$ |
| $\underline{SCap_s}$ | minimum capacity of storage technology $s$ |
| $SD_{i,g,t,e}$ | demand of product $i$ in sub-region $g$ in time $t$ in scenario $e$ |
| $SP_l$ | average speed of transportation mode $l$ |
| $sv$ | salvage value |
| $T$ | number of time intervals |
| $TCap_l$ | capacity of transportation mode $l$ |
| $TMC_{l,t}$ | cost of establishing transportation mode $l$ in period $t$ |
| $UPC_{i,p,g,t}$ | unit production cost |
| $USC_{i,s,g,t}$ | unit storage cost |

*Variables*

| | |
|---|---|
| $CF_{t,e}$ | cash flow in time $t$ in scenario $e$ |
| $DC_{t,e}$ | disposal cost in time $t$ in scenario $e$ |
| $DTS_{i,g,t,e}$ | amount of material $i$ delivered in sub-region $g$ in period $t$ in scenario $e$ |
| $FC_{t,e}$ | fuel cost in time $t$ in scenario $e$ |
| $FCI$ | fixed capital investment |
| $FOC_{t,e}$ | facility operating cost in time $t$ in scenario $e$ |
| $FTDC_{t,e}$ | fraction of the total depreciable capital in time $t$ in scenario $e$ |
| $GC_{t,e}$ | general cost in time $t$ in scenario $e$ |
| $LC_{t,e}$ | labor cost in time $t$ in scenario $e$ |
| $MC_{t,e}$ | maintenance cost in time $t$ in scenario $e$ |
| $NE_{t,e}$ | net earnings in time $t$ in scenario $e$ |
| $NP_{p,g,t}$ | number of plants operating with technology $p$ installed in sub-region $g$ in time $t$ |
| $NPV_e$ | net present value in scenario $e$ |
| $NS_{s,g,t}$ | number of storage facilities of type $s$ established in sub-region $g$ in time $t$ |
| $NT_{l,t}$ | number of transportation units $l$ |
| $PCap_{p,g,t}$ | capacity of technology $p$ in sub-region $g$ in time $t$ |
| $PCapE_{p,g,t}$ | capacity expansion of technology $p$ executed in sub-region $g$ in time $t$ |
| $Q_{i,l,g,g',t,e}$ | flow rate of material $i$ transported by mode $l$ from sub-region $g'$ to sub-region $g$ in time $t$ in scenario $e$ |
| $Rev_{t,e}$ | revenue in time $t$ in scenario $e$ |
| $SCap_{s,g,t}$ | capacity of storage $s$ in sub-region $g$ in time $t$ |
| $SCapE_{s,g,t}$ | capacity expansion of storage $s$ in sub-region $g$ in time $t$ |
| $ST_{i,s,g,t,e}$ | total inventory of material $i$ in sub-region $g$ stored by technology $s$ in time $t$ in scenario $e$ |
| $TOC_{t,e}$ | transport operating cost in time $t$ in scenario $e$ |
| $PE_{i,p,g,t,e}$ | production rate of material $i$ produced by technology $p$ in sub-region $g$ in time $t$ in scenario $e$ |
| $PT_{i,g,t,e}$ | total production rate of material $i$ in sub-region $g$ in time $t$ in scenario $e$ |
| $PU_{i,g,t,e}$ | purchase of material $i$ in sub-region $g$ in time $t$ in scenario $e$ |
| $X_{l,g,g',t}$ | binary variable (1 if a transportation link of type $l$ is established between sub-regions $g$ and $g'$ in period $t$, and 0 otherwise) |
| $W_{i,g,t,e}$ | amount of waste $i$ generated in sub-region $g$ in time $t$ in scenario $e$ |

2009). In 1976, the ethanol–gasoline blend became mandatory in Brazil. Since 2007, this blend should contain at least 25% of ethanol. With this energy policy, the percentage of renewable energy in the Brazilian energy matrix reached 45% in 2006 (Dias Leite, 2009). In 1978, the US Congress approved the Energy Tax Act to promote the usage of renewable energy through taxes and tax credits, and as result, USA overtook Brazil as the biggest ethanol producer in 2005, and by 2009, there were 170 ethanol distilleries with a total annual capacity 10.6 billion of gallons(RFA, 2009).

Vast investments, government sponsorship and tax incentives made Brazil and US the world leaders in ethanol production, currently covering about 90% of the ethanol production worldwide. Other countries have also started to adopt legislation and sponsor bioethanol programs. In 2007, the Argentinean Government published the Law 26,093 on biofuels, which has the target of achieving by 2010 a mix of 5% of ethanol in gasoline and 5% of bio-diesel in diesel. The Colombian Law 693 published in 2001 established a limit of 10% ethanol blend by 2006, and a 25% blend within 15 years. In Thailand, the goal is to achieve a 10% ethanol blend by 2011. In India, the Indian Ethanol Blended Petrol (EBP) program specifies a target of 5% ethanol gasoline blends. Canada also started to provided tax benefits for ethanol producers and consumers in 1992. The EU is no exception to this general trend, having established quantitative targets for the use of biofuels. Particularly, by 2010, it plans to replace 5.75% of diesel and gasoline by biofuels (Olsson, 2007).

The adoption of alternative energy sources has recently created a clear need for decision-support tools to assist in the design of infrastructures for biofuels production from biomass. Among the available methods, those based on mathematical programming have gained wider interest in the recent past. The main advantage of these tools is their capability of generating and assessing a very large number of process alternatives, from which the optimal one is selected. The prevalent approaches in this area have relied on linear programming (LP) and mixed-integer linear programming (MILP).

Several models have been proposed for optimizing bioethanol SCs. Yoshizaki et al. (1996) introduced an LP model to find the optimal distribution of sugarcane mills, fuel bases and consumer cites in southeastern Brazil. Kawamura et al. (2006) presented an LP model to minimize the transportation and external storage costs of the existing sugar/ethanol SC in Brazil. Ioannou (2005) applied an LP optimization model to reduce the transportation cost in the Greek sugar industry. The MILP model of Milan et al. (2006) minimizes the transportation cost of the sugarcane SC in Cuba. Dunnett et al. (2008) developed a combined production and logistic model to find the optimal configuration of lignocellulosic bioethanol SCs. Zamboni et al. (2009) presented a mathematical model to minimize the total daily cost of a static corn-based bioethanol SC. Mathematical programming methods associated with plantation planning and scheduling can also be found in the works by Grunow et al. (2007), Paiva and Morabito (2009), Colin (2009) and Higgins and Laredo (2006).

The environmental assessment of bioethanol production has gained wider interest in the recent past. Several models have been presented so far to optimize simultaneously the economic and environmental performance of bioethanol SCs. These approaches have mainly focused on reducing the greenhouse gas (GHG) emissions of the biofuel infrastructure. Zamboni et al. (2009) formulated a multi-objective optimization model to reduce the GHG emissions associated with the future corn-based Italian bioethanol network. Later, Giarola et al. (2011) extended this model by adding second generation bioethanol production technologies. It has been argued that minimizing exclusively the GHGs emission in the design of ethanol infrastructures can lead to solutions that reduce such emissions at the expense of increasing other negative effects (mainly the destruction of the native tropical ecosystems and soil erosion) (Scharlemann and Laurance, 2008; Vries et al., 2010). To overcome this limitation, Mele et al. (2011) developed a bi-criteria model that maximizes the profit and minimizes the life cycle environmental impact of combined sugar/bioethanol SCs. The latter criterion was measured through two environmental indicators: the eco-indicator 99 (Goedkoop and Spriensma, 1999), which accounts for eleven life cycle environmental impacts pertaining to several damage categories, and the global warming potential.

The studies mentioned above assume that all model parameters are perfectly known in advance (i.e., they are constant). In practice, however, some of them, especially the demand, show certain degree of variability and can therefore be regarded as uncertain. Various approaches have been proposed to formulate and solve optimization models with uncertain parameters (see Sahinidis, 2004). Particularly, two-stage stochastic programming is probably the prevalent approach to deal with optimization under uncertainty (Liu and Sahinidis, 1996). Two-stage stochastic formulations involve two types of decisions: first stage decisions that must be made before the realization of the uncertain parameters, and second stage decisions that are taken once the uncertainty is unveiled. The goal is to choose the first-stage variables in a way that the expected value of the objective function is maximized or minimized over all the scenarios. Robust optimization is an alternative approach to handle uncertainties that relies on the use of chance-constraints. Following this approach, the original robust stochastic model is typically substituted by a deterministic formulation with several equations representing the probabilistic statements expressed through chance constraints (Li et al., 2008). The main drawback of this technique is that it does not include second-stage variables, that is, it does not quantify the effect of each uncertain outcome when it materializes. Fuzzy programming (Zimmermann, 1991) is another approach to deal with uncertainties that relies on modeling the random parameters as fuzzy numbers and treating the model constraints as fuzzy sets.

To the best of our knowledge, there are only two works in the literature that have accounted for uncertainties in the optimization of biofuel infrastructures. Dal-Mas et al. (2011) proposed a scenario-based MILP model that maximizes the expected profit and minimizes the financial risk of the corn-to-ethanol production SC in Northern Italy. The model takes into account the uncertainty of the corn purchase cost and ethanol selling price. Kim et al. (2011) presented a two-stage MILP model for optimizing a bio-oil network in the SE region of the US under uncertainty in 14 key model parameters. The authors performed also a sensitivity analysis to estimate key factors affecting the SC performance.

This article introduces a novel two stage MILP formulation for the strategic planning of SCs for bioethanol and sugar production under demand uncertainty. To the best of our knowledge, this is the first contribution that addresses explicitly the uncertainty associated with the bioethanol and sugar demand and analyzes its impact on the optimal SC structure and economic performance of the network considering several risk metrics. A decomposition strategy based on the sample average approximation (SAA) (Verweij et al., 2003) algorithm is also presented to efficiently solve the underlying stochastic MILP. This algorithm provides as output a set of SC design alternatives that behave in different ways in the face of uncertainty.

The remainder of this article is organized as follows. In Section 2, the problem under study is formally stated, and

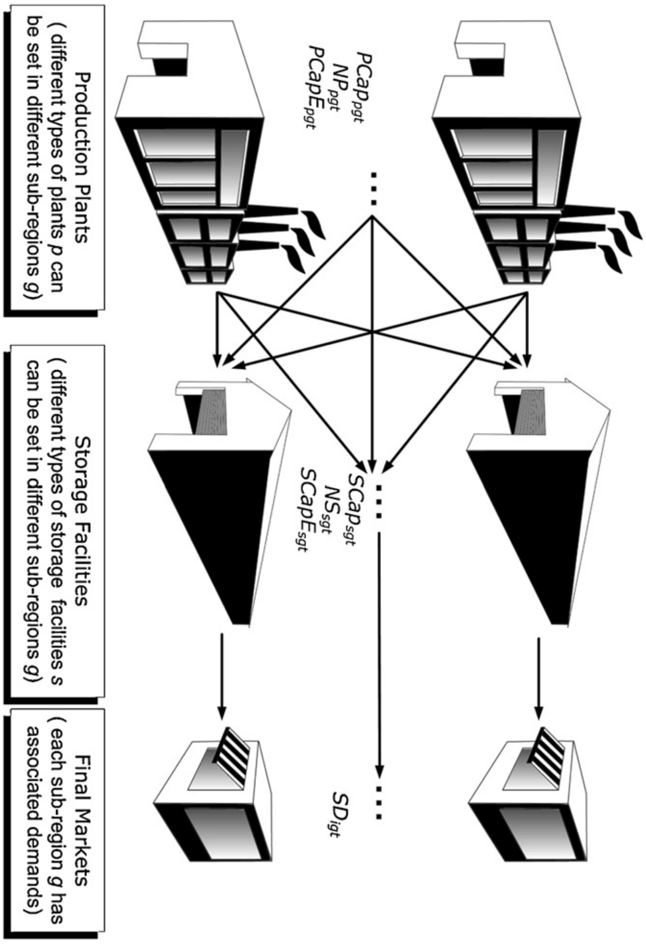


**Fig. 1 – Structure of the bioethanol/sugar SC.**

the assumptions made are briefly described. The problem data, decision variables and objectives are also listed at this point. In Section 3, we describe a two-stage stochastic model for the design and planning of bioethanol SCs that considers explicitly the demand variability. In Section 4, we introduce a decomposition method based on the SAA algorithm that provides approximate solutions to the multi-objective stochastic formulation in short CPU times. In Section 5, the proposed approach is applied to a real case study based on the sugarcane industry of Argentina, for which valuable insights are obtained. The conclusions of the work are finally drawn in the last section of the paper.

## 2. Problem statement

Fig. 1 depicts the SC structure we use in our work. We analyze integrated infrastructures for the combined production of ethanol and sugar, in which final products (ethanol, white and raw sugars) are stored in warehouses before being delivered to the final markets. Two different types of storage facilities are considered that are suitable for solid (S1) and liquid (S2) materials, respectively. The SC facilities can be located in different sub-regions, and are connected via transportation links. We consider three types of vehicles: heavy trucks for sugarcane (TR1), lorries for sugars (TR2), and tank trucks for ethanol and all types of vinasse (TR3).

The problem addressed in this article can be formally stated as follows. Given are a set of potential locations for the SC facilities, the capacity limitations associated with these technologies, the demand and prices of final products and raw materials and the investment and operating cost of the network. The demand is assumed to be uncertain, and it is described through a set of scenarios with a given probability of occurrence. The goal of the study is to determine the configuration of the SC along with the associated planning decisions that maximize its economic performance under uncertainty.

## 3. Stochastic mathematical model

### 3.1. *General features*

The general structure of the mathematical model presented next is based on previous works by the authors (see Guillén-Gosálbez and Grossmann, 2009 and Guillén-Gosálbez et al., 2009). Our model has been originally devised bearing in mind the main features of the sugarcane industry of Argentina, but it is general enough to be easily extended to any other supply chain with similar characteristics.

Argentina has abundant natural resources and an efficient agricultural sector (Ken and Wilder, 2010). Sugarcane, in particular, shows several appealing characteristics compared to other products, such as its resistance, rapid growth and uptake capacity for atmospheric carbon. This makes sugarcane a suitable feedstock for biofuels production. The main advantage of the production of ethanol from sugarcane is its positive energy balance (Goldemberg et al., 2008). Unfortunately, the use of ethanol in Argentina has the disadvantage of competing with sugar, because both of them share the same raw material. A key issue in the optimization of bioethanol infrastructures in Argentina is then the assessment of the interactions between both competing products.

The following assumptions, some of which are based on the particular features of the Argentinean sugarcane industry, are applied in the derivation of our model:

**Production.** It is assumed that the juice is extracted from sugarcane mainly by milling. Sugar mills use this juice to produce white sugar and raw sugar. There are two technologies that follow the "sugarcane-to-sugar" pathway. One of them generates molasses (T1) as a byproduct, whereas the other one produces a secondary honey (T2) in addition to sugars. These two byproducts differ in their sucrose content. Molasses is a viscous dark honey whose low sucrose content cannot be separated by crystallization, while the secondary honey is a honey with a larger amount of sucrose that leaves the sugar mill before being exhausted by crystallization. Anhydrous ethanol can be produced by fermentation and subsequent dehydration of different process streams: molasses (T3), honey (T4), and sugarcane juice (T5). Thus, the model considers a total of five different technologies, two for sugar production and three types of distilleries. The details of each technology, including the mass balance coefficients, are shown in Fig. 2, where residuals, loses and wastes are omitted. We assume that the bagasse is completely utilized for internal purposes, so there is a total of nine materials classified into raw materials, by-products, and final products: sugarcane, ethanol, molasses, honey, white sugar, raw sugar, vinasse type 1, vinasse type 2 and vinasse type 3. Each plant incurs fixed capital and operating cost, and can be expanded in capacity over time in order to follow a specific demand pattern.

**Storage.** The model includes two different types of storage facilities: warehouses for liquid products (S1), and warehouses for solid materials (S2). For each storage facility type, we consider specific fixed capital and unit storage costs, along with

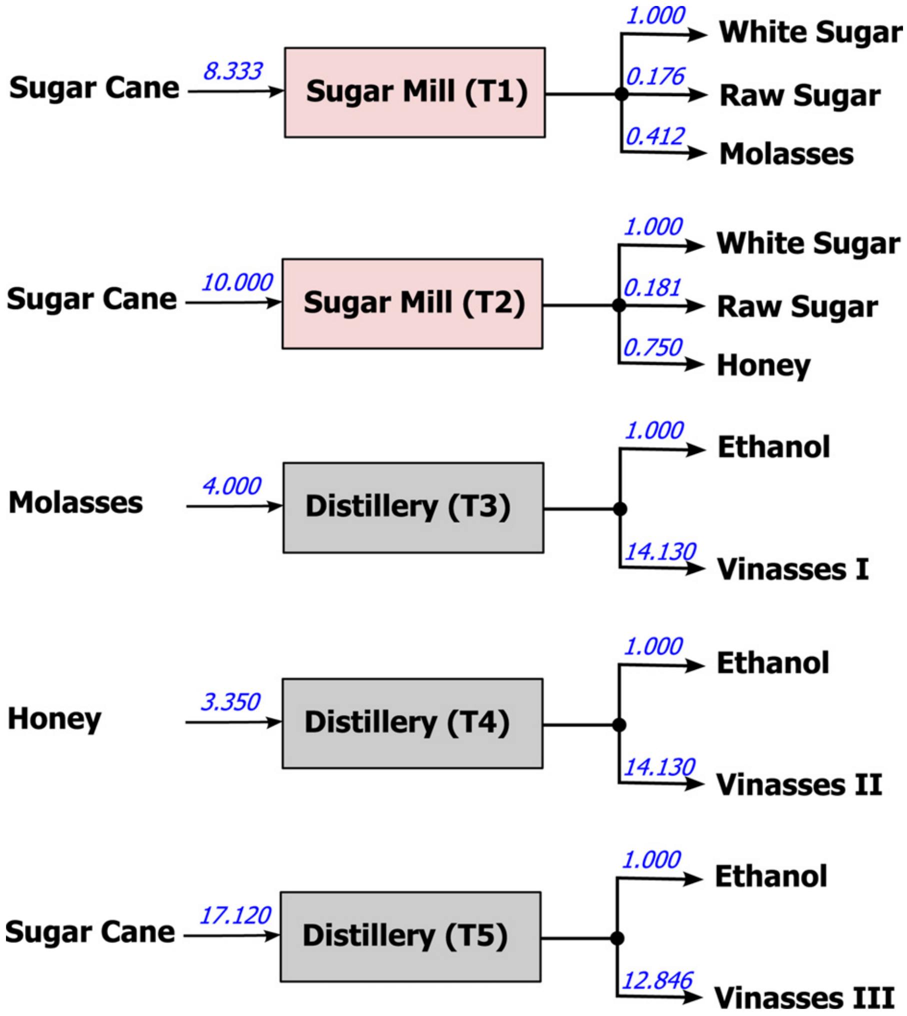


**Fig. 2 – Set of production technologies.**

lower and upper limits on its capacity expansions. Similarly, as with the plants, the storage capacity might be expanded in order to follow changes in the demand as well as in the supply.

**Transportation.** Transportation units deliver the final products to the customers, supply the production plants with raw materials, and dispose the process wastes. The model assumes that the materials can be transported by three different types of trucks: heavy trucks with open-box bed for sugar cane (TR1), medium trucks for sugar (TR2), and tank trucks for liquid products (TR3). Each transportation mode has fixed capital and unit transportation costs, and lower and upper limits on its capacity. Both storage and transportation modes considered in the model are shown in Fig. 3.

### 3.2. *Model structure: two-stage stochastic programming*

A number of deterministic models have been published to model and optimize the structure of SCs (Chen and Wang, 1997; Timpe and Kallrath, 2000; Bok et al., 2000; Almansoori and Shah, 2006). These models assume that all model parameters are perfectly known in advance and do not show variability. In practice, however, there are numerous technical and market uncertainties that affect the calculations. One of the most important sources of uncertainty in any SC is the product demand. Failure to properly account for product demand fluctuations may result in either unsatisfied customer demand or excess of products. The first scenario leads to a loss of potential revenues and market share, whereas the second one generates large inventory costs.

We introduce next a two-stage stochastic programming MILP model to address the strategic planning of biofuels SCs under demand uncertainty. The equations of the model are roughly classified into three main blocks: mass balance equations, capacity constraints and objective function equations. With regard to the variables, these are divided into two main groups:

- *First-stage*, or *here-and-now* decisions, which are taken before the uncertainty unveils. In our work, the SC design decisions, namely the number of production, storage and transportation units, and their initial capacities and capacity expansions over the time horizon are considered as first stage decisions. The reason for this is that we assume that they are taken at the beginning of the time horizon, before the demand is known.
- *Second-stage*, or *wait-and-see* decisions, which are taken once the uncertainty is materialized. They include the amount of products to be produced and stored, the flows of materials transported among the SC entities and the product sales. As will be shown later in the article, the second-stage variables include a subscript *e* that denotes the particular scenario realization for which they are defined.

The sections that follow describe in detail all the variables and constraints of the model.

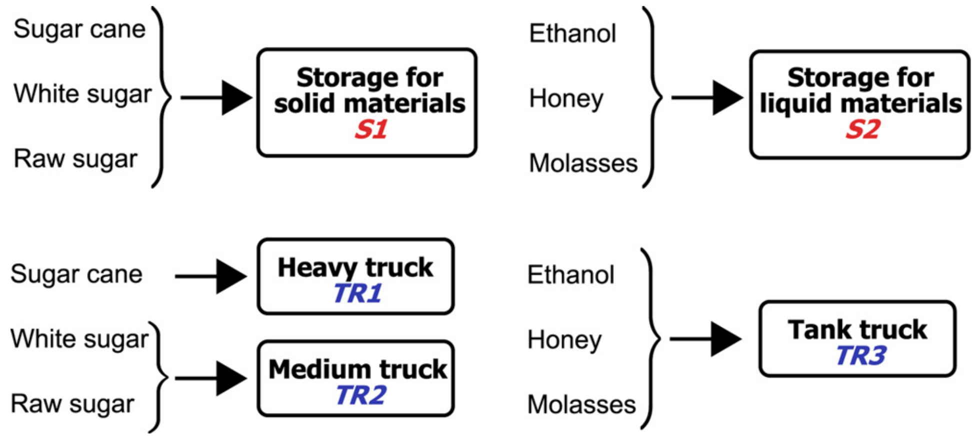


**Fig. 3 – Set of storage and transportation technologies.**

### 3.3. *Mass balance constraints*

The overall mass balance for each sub-region is enforced via Eq. (1). For every material form $i$ and scenario $e$, the initial inventory kept in sub-region $g$ ($ST_{i,s,g,t-1,e}$) plus the amount produced ($PT_{i,g,t,e}$), the amount of raw materials purchased ($PU_{i,g,t,e}$) and the input flow rate from other facilities in the SC ($Q_{i,l,g',g,t,e}$) must equal the final inventory ($ST_{i,s,g,t,e}$) plus the amount delivered to the customers ($DTS_{i,g,t,e}$) plus the output flow to other facilities in the SC ($Q_{i,l,g,g',t,e}$) and the amount of waste ($W_{i,g,t,e}$).

$$\sum_{s\in SI(i)} ST_{i,s,g,t-1,e} + PT_{i,g,t,e} + PU_{i,g,t} + \sum_{l\in LI(i)}\sum_{g'\neq g} Q_{i,l,g',g,t,e} = \sum_{s\in SI(i)} ST_{i,s,g,t,e} + DTS_{i,g,t,e} + \sum_{l\in LI(i)}\sum_{g'\neq g} Q_{i,l,g,g',t,e} + W_{i,g,t,e} \quad \forall i, g, t, e \tag{1}$$

In this equation, $SI(i)$ represents the set of technologies that can be used to store product $i$, whereas $LI(i)$ is the set of transport modes suitable for product $i$.

For each scenario $e$, the total production rate of material $i$ in sub-region $g$ is determined from the production rates associated with each technology $p$ installed in that sub-region ($PE_{i,p,g,t,e}$):

$$PT_{i,g,t,e} = \sum_{p} PE_{i,p,g,t,e} \quad \forall i, g, t, e \tag{2}$$

The production rates of byproducts and the consumption rates of raw materials associated with each technology are calculated in each scenario $e$ from the material balance coefficient $\rho_{pi}$, and the production rate of the main product:

$$PE_{i,p,g,t,e} = \rho_{p,i} PE_{i',p,g,t,e} \quad \forall i, p, g, t, e \quad \forall i' \in IM(p) \tag{3}$$

In this equation, $IM(p)$ represents the set of main products associated with each technology. Fig. 2 shows the material balance coefficients of the main products (white sugar and ethanol). Note that these parameters are typically normalized to 1.

For each scenario $e$ and time interval $t$, the purchases of sugarcane are limited by the capacity of the existing sugarcane plantation in sub-region $g$:

$$PU_{i,g,t,e} \leq CapCrop_{g,t} \quad i = \text{Sugarcane}, \forall g, t, e \tag{4}$$

The total inventory of product $i$ stored at the end of the time interval $t$ in each scenario $e$ ($ST_{i,s,g,t,e}$) must be less than or equal to the available storage capacity ($SCap_{s,g,t}$):

$$\sum_{i\in IS(s)} ST_{i,s,g,t,e} \leq SCap_{s,g,t} \quad \forall s, g, t, e \tag{5}$$

The average inventory in scenario $e$ ($AIL_{i,g,t,e}$) is a function of the amount delivered to the customers and the storage period $\beta$:

$$AIL_{i,g,t,e} = \beta DTS_{i,g,t,e} \quad \forall i, g, t, e \tag{6}$$

The storage capacity ($SCap_{s,g,t}$) that should be established in a sub-region in order to cope with fluctuations in both supply and demand, is twice the summation of the average inventory levels of products $i$ (Simchi-Levi et al., 2000) in each scenario $e$:

$$2AIL_{i,g,t,e} \leq \sum_{s\in SI(i)} SCap_{s,g,t} \quad \forall i, g, t, e \tag{7}$$

Furthermore, the amount of product $i$ delivered to the final markets located in region $g$ in scenario $e$ and period $t$ should be less than or equal to the corresponding demand in that region ($SD_{i,g,t,e}$):

$$DTS_{i,g,t,e} \leq SD_{i,g,t,e} \quad \forall i, g, t, e \tag{8}$$

### 3.4. *Capacity constraints*

The production rate of each technology $p$ in sub-region $g$ and scenario $e$ must lie between the minimum desired percentage of the available technology that must be utilized, $\tau$, multiplied by the existing capacity (represented by the continuous variable $PCap_{p,g,t}$) and the maximum capacity:

$$\tau PCap_{p,g,t} \leq PE_{i,p,g,t,e} \leq PCap_{p,g,t} \quad \forall i, p, g, t, e \tag{9}$$

The capacity of technology $p$ in any time period $t$ is calculated from the existing capacity at the end of the previous period and the expansion in capacity, $PCapE_{p,g,t}$, carried out in period $t$:

$$PCap_{p,g,t} = PCap_{p,g,t-1} + PCapE_{p,g,t} \quad \forall p, g, t \tag{10}$$

Eq.(11) limits the capacity expansion $PCapE_{p,g,t}$ between upper and lower bounds, which are calculated from the number of plants installed in the sub-region ($NP_{g,p,t}$) and the minimum and maximum capacity associated with each technology $p$ ($\underline{PCap_p}$ and $\overline{PCap_p}$, respectively).

$$\underline{PCap_p} NP_{p,g,t} \leq PCapE_{p,g,t} \leq \overline{PCap_p} NP_{p,g,t} \quad \forall p, g, t \tag{11}$$

The storage capacity must lie within certain lower and upper bounds that are calculated from the number of storage facilities installed in sub-region $g$ ($NS_{s,g,t}$) and the minimum and maximum storage capacities ($\underline{SCap_s}$ and $\overline{SCap_s}$, respectively) associated with each storage technology:

$$\underline{SCap_s} NS_{s,g,t} \leq SCapE_{s,g,t} \leq \overline{SCap_s} NS_{s,g,t} \quad \forall s, g, t \tag{12}$$

The capacity of a storage technology $s$ in region $g$ and time period $t$ is determined from the existing capacity at the end of the previous period and the expansion in capacity in the current period ($SCapE_{s,g,t}$):

$$SCap_{s,g,t} = SCap_{s,g,t-1} + SCapE_{s,g,t} \quad \forall s, g, t \tag{13}$$

The materials flows in scenario $e$ are constrained within some minimum and maximum allowable capacity limits ($\underline{Q_l}$ and $\overline{Q_l}$, respectively):

$$\underline{Q_l} X_{l,g,g',t} \leq \sum_{i \in IL(l)} Q_{i,l,g,g',t,e} \leq \overline{Q_l} X_{l,g,g',t} \quad \forall l, t, g, g' (g' \neq g), e \tag{14}$$

In this equation, $IL(l)$ represents the set of materials that can be transported via transportation mode $l$.

### 3.5. *Objective function*

The model shows a different economic performance in each scenario. In our case, this economic performance is measured through the net present value ($NPV$). Thus, one objective of the mathematical formulation is to maximize the expected value of the resulting $NPV$ distribution. Certain risk metrics are also appended to the objective function in order to control the probability of unfavorable scenarios with low $NPV$ values. The sections that follows describe how these metrics are determined.

#### 3.5.1. *Expected NPV*

One of the objectives of the model is to maximize the expected $NPV$. This metric is determined as follows:

$$E[NPV] = \sum_e pr_e NPV_e \tag{15}$$

where $pr_e$ is the probability of scenario $e$, and $NPV_e$ is the net present value attained in the same scenario. The latter term is determined from the cash flows ($CF_{t,e}$) generated in each of the time intervals $t$ in which the total time horizon is divided:

$$NPV_e = \sum_t \frac{CF_{t,e}}{(1+ir)^{t-1}} \quad \forall e \tag{16}$$

In this equation, $ir$ represents the interest rate. The cash flow in period $t$ is determined from the net earnings $NE_{t,e}$ (i.e., profit after taxes), and the fraction of the total depreciable capital ($FTDC_t$) that corresponds to that period as follows:

$$CF_{t,e} = NE_{t,e} - FTDC_t \quad t = 1, \ldots, T-1, \forall e \tag{17}$$

When determining the cash flow of the last time period ($t = T$), we consider that part of the total fixed capital investment ($FCI$) will be recovered at the end of the time horizon. This amount, which represents the salvage value of the network ($sv$), may vary from one type of industry to another.

$$CF_{t,e} = NE_{t,e} - FTDC_t + sv FCI \quad t = T, \forall e \tag{18}$$

The net earnings are given by the difference between the incomes ($Rev_{t,e}$) and the facility operating ($FOC_{t,e}$), and transportation cost ($TOC_{t,e}$), as stated in Eq.(19):

$$NE_{t,e} = (1-\varphi)(Rev_{t,e} - FOC_{t,e} - TOC_{t,e}) + \varphi DEP_{t,e} \quad \forall t, e \tag{19}$$

In this equation, $\varphi$ denotes the tax rate. The depreciation term is calculated with the straight-line method:

$$DEP_t = \frac{(1-sv)FCI}{T} \quad \forall t \tag{20}$$

where $FCI$ denotes the total fixed cost investment, which is determined from the capacity expansions made in plants and warehouses as well as the purchases of transportation units during the entire time horizon as follows:

$$\begin{aligned} FCI = & \sum_p \sum_g \sum_t (\alpha^{PL}_{p,g,t} NP_{p,g,t} + \beta^{PL}_{p,g,t} PCapE_{p,g,t}) \\ & + \sum_s \sum_g \sum_t (\alpha^{S}_{s,g,t} NS_{s,g,t} + \beta^{S}_{s,g,t} SCapE_{s,g,t}) \\ & + \sum_l \sum_t (NT_{l,t} TMC_{l,t}) \end{aligned} \tag{21}$$

Here, the parameters $\alpha^{PL}_{p,g,t}$, $\beta^{PL}_{p,g,t}$ and $\alpha^{S}_{sgt}$, $\beta^{S}_{sgt}$ are the fixed and variable investment terms associated with plants and warehouses, respectively. On the other hand, $TMC_{l,t}$ is the purchase cost associated with the transportation mode $l$. The average number of trucks required to satisfy a certain flow between different sub-regions is calculated from the flow rate of products between the sub-regions, the transportation mode availability ($avl_l$), the capacity of a transport container, the average distance traveled between the sub-regions, the average speed, and the loading/unloading time, as stated in Eq. (22):

$$\sum_{t \leq T} NT_{l,t} = \sum_{i \in IL(l)} \sum_g \sum_{g' \neq g} \sum_t \frac{Q_{i,l,g,g',t}}{avl_l TCap_l} \left( \frac{2EL_{g,g'}}{SP_l} + LUT_l \right) \quad \forall l \tag{22}$$

The revenues are determined from the sales of final products and the corresponding prices ($PR_{i,g,t}$):

$$Rev_{t,e} = \sum_{i \in SEP} \sum_{g} DTS_{i,g,t,e} PR_{i,g,t} \quad \forall t, e \tag{23}$$

In this equation, $SEP(i)$ represents the set of materials $i$ that can be sold. The facility operating cost is obtained by multiplying the unit production and storage costs ($UPC_{i,p,g,t}$ and $USC_{i,s,g,t}$, respectively) with the corresponding production rates and average inventory levels, respectively. This term includes also the disposal cost ($DC_{t,e}$):

$$\begin{aligned} FOC_{t,e} = & \sum_{i \in IM(p)} \sum_{p} \sum_{g} UPC_{i,p,g,t} PE_{i,p,g,t,e} \\ & + \sum_{i \in IS(s)} \sum_{s} \sum_{g} USC_{i,s,g,t} AIL_{i,g,t,e} + DC_{t,e} \quad \forall t, e \end{aligned} \tag{24}$$

The disposal cost is a function of the amount of waste generated and landfill tax ($LT_{ig}$):

$$DC_{t,e} = \sum_{i} \sum_{g} W_{i,g,t,e} LT_{ig} \quad \forall t, e \tag{25}$$

The transportation cost includes the fuel ($FC_{t,e}$), labor ($LC_{t,e}$), maintenance ($MC_{t,e}$) and general ($GC_{t,e}$) costs:

$$TOC_{t,e} = FC_{t,e} + LC_{t,e} + MC_{t,e} + GC_{t,e} \quad \forall t, e \tag{26}$$

The fuel cost is a function of the fuel price ($FP_{l,t}$) and fuel usage:

$$FC_{t,e} = \sum_{i \in IL(l)} \sum_{g} \sum_{g' \neq g} \sum_{l} \left[ \frac{2EL_{g,g'} Q_{i,l,g,g',t,e}}{FE_l TCap_l} \right] FP_{l,t} \quad \forall t, e \tag{27}$$

In Eq. (27), the fractional term represents the fuel usage, which is determined from the total distance traveled in a trip ($2EL_{g,g'}$), the fuel consumption of transport mode $l$ ($FE_l$) and the number of trips made per time period ($Q_{i,l,g,g',t,e}/TCap_l$). This equation considers that the transportation units operate only between two predefined sub-regions. Furthermore, as shown in Eq. (28), the labor transportation cost is a function of the driver wage ($DW_{l,t}$) and total delivery time (term inside the brackets):

$$\begin{aligned} LC_{t,e} = & \sum_{i \in IL(l)} \sum_{g} \sum_{g' \neq g} \sum_{l} DW_{l,t} \left[ \frac{Q_{i,l,g,g',t,e}}{TCap_l} \left( \frac{2EL_{g,g'}}{SP_l} + LUT_l \right) \right] \\ & \times \forall t, e \end{aligned} \tag{28}$$

The maintenance cost accounts for the general maintenance of the transportation units, and is a function of the cost per unit of distance traveled ($ME_l$) and total distance driven:

$$MC_{t,e} = \sum_{i \in IL(l)} \sum_{g} \sum_{g' \neq g} \sum_{l} ME_l \frac{2EL_{g,g'} Q_{i,l,g,g',t,e}}{TCap_l} \quad \forall t, e \tag{29}$$

Finally, the general cost includes the transportation insurance, license and registration, and outstanding finances. It can be determined from the unit general expenses ($GE_{l,t}$) and number of transportation units ($NT_{l,t}$), as follows:

$$GC_t = \sum_{l} \sum_{t' \leq t} GE_{lt} NT_{lt'} \quad \forall t \tag{30}$$

The total capital investment can be constrained to be lower than an upper limit, as stated in Eq. (31):

$$FCI \leq \overline{FCI} \tag{31}$$

The model assumes that the depreciation is linear over the time horizon, so the amount of capital investment paid in each time period ($FTDC_t$) is calculated as follows:

$$FTDC_t = \frac{FCI}{T} \quad \forall t \tag{32}$$

While $NPV$ has been thoroughly used in several SC designs, caution ought to be exercised. In fact, as pointed out by Bagajewicz (2008), maximizing $NPV$ without control of the capital to invest can lead to solutions that have marginal profit far inferior in terms of return of investment ($ROI$), which is an alternative objective that one could use. In our case, to overcome this limitation, we limit the $FCI$.

### 3.6. *Probabilistic metrics for financial risk management*

The variability of the objective function can be controlled by adding to the model a set of constraints that measure the probability of not attaining a predefined target value $\Omega$. The calculation of these probabilities requires the definition of the binary variable $Z_e$. This variable takes the value of 1 if the $NPV$ attained in scenario $e$ is below the target level $\Omega$, and it is 0 otherwise. The definition of such a variable is enforced via the following constraints:

$$NPV_e \leq \Omega + M(1 - Z_e) \quad \forall e \tag{33}$$

$$NPV_e \geq \Omega - MZ_e \quad \forall e \tag{34}$$

These equations work as follows. If the binary variable takes a value of 1, then constraint Eq. (33) will force the $NPV$ to be lower than the target value in scenario $e$, whereas constraint Eq. (34) will be inactive. If the binary variable is 0, then Eq. (33) will be inactive and constraint Eq. (34) will ensure that the $NPV$ in that particular scenario lies above the target value. The probability of having an $NPV$ below $\Omega$ is calculated as follows:

$$Prob[NPV \leq \Omega_k] = \sum_{e} pr_e Z_{k,e} \tag{35}$$

where $pr_e$ denotes the probability of scenario $e$. An example of the definition of these probabilistic metrics in a particular stochastic problem is given in Fig. 4. This figure depicts the cumulative probability curve associated with a given SC design, considering a stochastic formulation with 100 scenarios, each one corresponding to a different materialization of the uncertain parameter (i.e., the demand). Assume that the target $\Omega$ is equal to US\$350 million. For this particular SC structure, there are 14 scenarios out of 100 with an $NPV$ below this

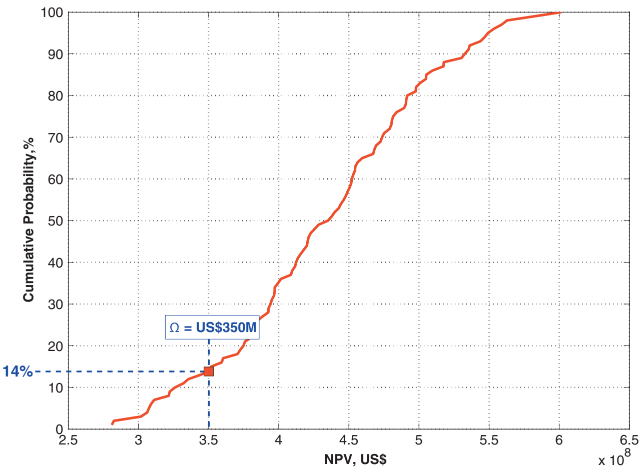


Fig. 4 – Cumulative probability curves.

target value (i.e., the probability of not exceeding the target value is 14%).

In general, the shape and slope of this cumulative probability curve can be manipulated according to the decision-maker's preferences. This can be done by properly adjusting the decisions associated with the SC design and operation. Fig. 5 depicts two cumulative probability curves associated with two different SC topologies. Design A shows lower probabilities of small and high *NPV*s, which would make it appealing for risk-averse decision-makers. On the other hand, design B might be the preferred alternative for risk-takers decision-makers, as it leads to larger probabilities of high *NPV*s at the expense of increasing as well the probability of low benefits.

A widely used risk metric is the value at risk (*VaR*) that can be defined as the difference between *E*[*NPV*] and the *NPV* value corresponding to a certain level of risk. In this study, this level is set to 5%. The symmetrically opposite measure of risk is the opportunity value (*OV*) (discussed by Aseeri and Bagajewicz, 2004), or upside potential that corresponds to the difference between the *NPV* at 95% risk and the expected value of *NPV*. Fig. 5 presents the calculation of *VaR* and *OV* for the aforementioned risk-averse and risk-taker cumulative probability curves.

The main disadvantage of both *VaR* and *OV* measures is that they cannot represent the behavior of the entire risk curve.

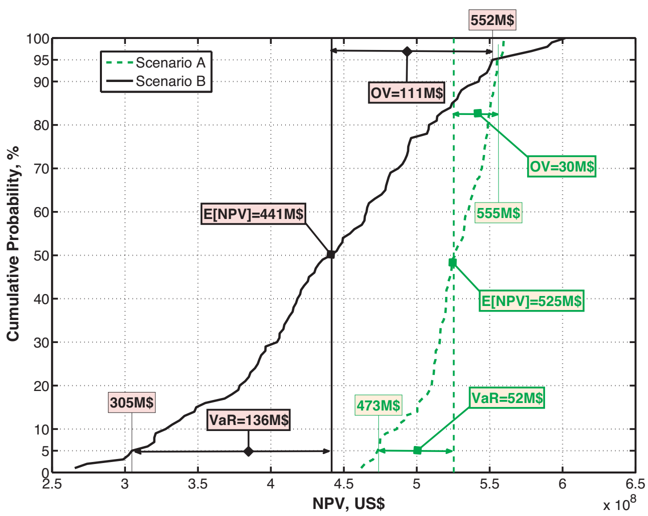


Fig. 5 – Value at risk (VaR) vs. opportunity value (OV).

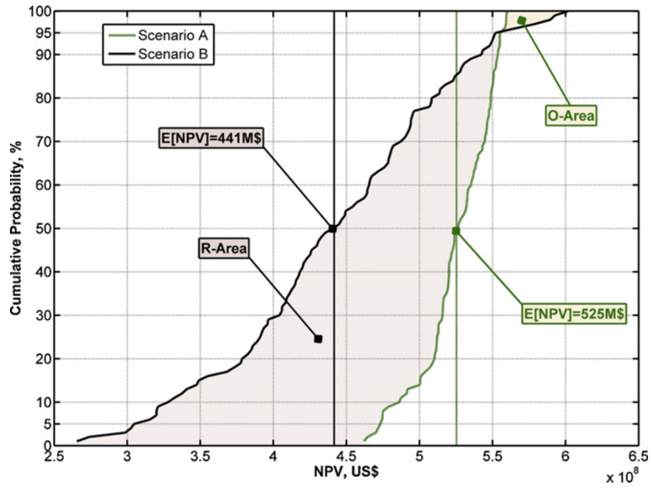


Fig. 6 – Risk area ratio (RAR).

Aseeri and Bagajewicz (2004) also proposed the use of the risk area ratio (*RAR*), which compares the areas between the risk curves corresponding to the reference plan with better *E*[*NPV*] and the alternative plan being evaluated. The proposed metric is the ratio of the opportunity area (O-Area) enclosed by the two curves above their intersection, to the risk area (R-Area) enclosed by the two curves below their intersection (see Fig. 6). The *RAR* is therefore mathematically defined as follows:

$$RAR = \frac{\mathrm{O-Area}}{\mathrm{R-Area}} \tag{36}$$

Aseeri and Bagajewicz (2004) claim that a good risk-reduced plan is one with a *RAR* as close to 1 as possible. Rather than solving a multi-objective model that seeks to optimize the aforementioned risk metrics, we propose herein to apply a method based on the sample average approximation algorithm (Verweij et al., 2003; Aseeri and Bagajewicz, 2004; Barbaro and Bagajewicz, 2004). As will be shown later in the article, our approach allows for the identification of SC configurations with different economic performance (measured according to the risk metrics mentioned above) in the face of uncertainty. From these alternatives, decision-makers should choose the best one according to their preferences. The method is described in detail in the following section.

## 4. Solution method: sample average approximation

The algorithm used to approximate the solution of the stochastic problem entails the calculation of two models that are solved in an iterative manner. A reduced-space stochastic model defined for only one scenario is solved in first place. This provides the values of the strategic and planning decision variables of the problem for that particular scenario. The original stochastic problem (with all the scenarios included) is then solved maximizing the expected *NPV* and fixing the first stage variables to the values provided by the reduced-space stochastic model. Hence, for each set of design variables corresponding to the solution of the reduced-space stochastic model defined for a specific scenario, we construct a risk curve. This procedure is repeated until there are no more scenarios to be explored.

After solving the reduced-space stochastic model for all the scenarios, we obtain a set of risk curves that are next filtered in

**Table 1 – Expected demand, ton/year.**

| Sub-region | Product form | | |
|---|---|---|---|
| | White sugar | Raw sugar | Ethanol |
| Córdoba | 84,126 | 42,063 | 92,539 |
| Mesopotamia | 84,126 | 42,063 | 92,539 |
| Buenos Aires | 455,884 | 227,942 | 501,472 |
| Cuyo | 72,108 | 36,054 | 79,319 |
| North | 39,960 | 19,980 | 43,956 |
| North West | 47,872 | 23,936 | 52,659 |
| Tucumán | 37,156 | 18,578 | 40,871 |
| Santa Fe | 81,122 | 40,561 | 89,234 |
| La Pampa | 8,413 | 4,206 | 9,254 |
| Santiago | 21,733 | 10,866 | 23,906 |
| West | 18,327 | 9,164 | 20,160 |
| Patagonia | 49,174 | 24,587 | 54,091 |

**Table 2 – Distances between sub-regions, km.**

| | Córdoba | Mesopotamia | Buenos Aires | Cuyo | North | North West | Tucumán | Santa Fe | La Pampa | Santiago | West | Patagonia |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Córdoba | 0 | 900 | 768 | 680 | 880 | 844 | 552 | 340 | 618 | 439 | 433 | 1196 |
| Mesopotamia | 900 | 0 | 990 | 1490 | 20 | 830 | 794 | 540 | 1388 | 635 | 857 | 1774 |
| Buenos Aires | 768 | 990 | 0 | 1137 | 1010 | 1599 | 1286 | 541 | 664 | 1127 | 1173 | 924 |
| Cuyo | 680 | 1490 | 1137 | 0 | 1470 | 1311 | 1001 | 930 | 789 | 1007 | 725 | 1342 |
| North | 880 | 20 | 1010 | 1470 | 0 | 810 | 774 | 540 | 1368 | 618 | 820 | 1756 |
| North West | 844 | 830 | 1599 | 1311 | 810 | 0 | 310 | 1077 | 1462 | 472 | 533 | 2066 |
| Tucumán | 552 | 794 | 1286 | 1001 | 774 | 310 | 0 | 764 | 1170 | 159 | 221 | 1765 |
| Santa Fe | 340 | 540 | 541 | 930 | 540 | 1077 | 764 | 0 | 828 | 605 | 777 | 1218 |
| La Pampa | 618 | 1388 | 664 | 789 | 1368 | 1462 | 1170 | 828 | 0 | 1050 | 1065 | 580 |
| Santiago | 439 | 635 | 1127 | 1007 | 618 | 472 | 159 | 605 | 1050 | 0 | 234 | 1634 |
| West | 433 | 857 | 1173 | 725 | 820 | 533 | 221 | 777 | 1065 | 234 | 0 | 1645 |
| Patagonia | 1196 | 1774 | 924 | 1342 | 1756 | 2066 | 1765 | 1218 | 580 | 1634 | 1645 | 0 |

order to discard those that are dominated by at least another one. One solution A is dominated by another solution B if its probability curve lies entirely above that of B. Note that this implies that for any probability level, A will always lead to lower benefits than B. In other words, A will be better considering the whole range of probability levels. From the set of non-dominated solutions, decision-makers should choose the one that better fits his/her preferences.

The detailed steps of the algorithm are as follows:

1. Set counter *ctr* equal to 1.
2. Solve the stochastic model defined for the scenario whose ordinality is equal to *ctr*.
3. Fix the first stage variables, and solve the stochastic model with all the scenarios included maximizing the expected *NPV*.
4. If $ctr = |E|$ then go to step 5, otherwise make $ctr = ctr + 1$ and go to step 2.
5. Filter the probability curves of the solutions obtained so far by removing the curves dominated by at least another one.
6. End.

Note that the algorithm presented above has been used successfully in a variety of applications to address optimization problems under uncertainty (Whitnack et al., 2009; Lakkhanawat and Bagajewicz, 2008; Lavaja et al., 2006; Pongsakdi et al., 2006; Lavaja and Bagajewicz, 2005, 2004; Guillén-Gosálbez et al., 2005, 2005, 2003; Aseeri et al., 2004; Barbaro and Bagajewicz, 2004; Bonfill et al., 2004; Romero et al., 2003; Bagajewicz and Barbaro, 2003; Koppol and Bagajewicz, 2003; Mele et al., 2003).

## 5. Case study

We illustrate the capabilities of the proposed approach through a case study based on the sugarcane industry of Argentina. The problem considers 12 sub-regions each one with an associated demand of sugar and ethanol. We should clarify that Argentina is in fact divided into 24 political provinces, some of which have been merged to simplify the calculations. The sub-region “Mesopotamia” comprises the provinces of Corrientes, Misiones and Entre Ríos. The province of Buenos Aires and Buenos Aires city have been merged into the sub-region “Buenos Aires”. The sub-region “Cuyo” includes the provinces of Mendoza, San Luis and San Juan. The sub-region “Patagonia” includes the 5 southernmost

**Table 3 – Sugarcane capacity, ton/year.**

| Sub-region | Capacity |
|---|---|
| Mesopotamia | 62,040 |
| North West | 6,392,000 |
| Tucumán | 12,220,000 |
| Santa Fe | 125,960 |

**Table 5 – Parameters used to evaluate the capital cost for different production technologies.**

| | $\alpha^{PL}_{pgt}$, \$ | $\beta^{PL}_{pgt}$, \$ · year/ton |
|---|---|---|
| T1 | 5,350,000 | 535 |
| T2 | 5,350,000 | 535 |
| T3 | 7,710,000 | 771 |
| T4 | 7,710,000 | 771 |
| T5 | 9,070,000 | 907 |

**Table 6 – Parameters used to evaluate the capital cost for different storage technologies.**

| | $\alpha^{S}_{sgt}$, \$ | $\beta^{S}_{sgt}$, \$ · year/ton |
|---|---|---|
| S1 | 1,220,000 | 122 |
| S2 | 18,940,000 | 1894 |

provinces of Neuquén, Río Negro, Chubut, Santa Cruz and Tierra del Fuego. The provinces of Chaco and Formosa are merged in the sub-region "North", whereas Jujuy and Salta are included in the region "North West". The sub-region "West" includes the provinces of Catamarca and La Rioja. The remaining sub-regions correspond to the homonymous Argentinean provinces.

All these sub-regions along with the mean values of the associated demand are shown in Table 1. The entire set of demand values is provided as supplementary material. The prices for white sugar, raw sugar and ethanol are equal to US\$537/ton, US\$375/ton and US\$860/ton, respectively. Distances between regions have been determined considering the capitals of the corresponding provinces and the main roads connecting them. These data are listed in Table 2. We assume that each region has an associated sugarcane crop capacity. Particularly, sugarcane plantations are situated in only five Argentinean provinces, whose production capacities are represented in Table 3. The length of the planning horizon is equal to 3 years.

The upper bound on the capital investment is US\$1.5 billion. The minimum and maximum production capacities of each technology are listed in Table 4. The minimum and maximum storage capacities for liquid and solid materials are assumed to be 50 and 2 billion tons, respectively. Fixed and variable investment coefficients for different production and storage modes are listed in Tables 5 and 6, respectively. Unit production cost for sugar and ethanol are equal to US\$265/ton and US\$317/ton, respectively. The unit storage cost is US\$0.365/(ton·year) for all types of materials. The parameters used to calculate the capital and operating cost for different transportation modes can be found in Table 7. The minimum flow rate of each transportation mode is assumed to be equal to the minimum capacity of the corresponding transportation mode, whereas the maximum flow rates for heavy trucks, medium trucks and tanker trucks are 6.25, 6.25 and 6.00 million tons per year, respectively.

The stochastic model with 100 scenarios was written in GAMS (Rosenthal, 2008) and solved with the MILP solver CPLEX 11.0 on a HP Compaq DC5850 desktop PC with an AMD Phenom 8600B, 2.29 GHz triple-core processor, and 2.75 Gb of RAM. Each deterministic model was solved using the "rolling horizon" strategy introduced in a previous work (Kostin et al., 2011). Specifically, we solved two different case studies that differ in the demand variability. These cases are described in detail next.

### 5.1. *High variance in ethanol demand*

In this first case, we consider high and low variabilities for ethanol and sugar demand, respectively. Both parameters are assumed to follow normal distributions with a standard deviation of 30% for ethanol and 5% for sugar.

The resulting non-dominant cumulative risk curves obtained by applying our algorithm are shown in Fig. 7a. Note that each of these curves represents a different SC configuration and associated set of planning decisions for the entire time horizon. As observed, the *NPV* values lie in the interval US\$249–616 million. In the figure, we have identified different curves of interest for decision-makers. These are the one with maximum *E*[*NPV*], the deterministic solution (i.e., the one calculated with the deterministic formulation solved for the mean demand), the upper bound risk curve and two curves that may be appealing for risk-averse and risk-takers decision-makers. Let us clarify that the upper bound risk curve does not represent any particular SC configuration. This curve is constructed by plotting the best *NPV* that could be attained in each scenario (i.e., the *NPV* of the best SC configuration for that particular scenario realization). Hence, the upper bound curve represents the best performance that a SC could exhibit in the face of uncertainty (Barbaro and Bagajewicz, 2004).

As observed, the solutions behave in different ways in the face of uncertainty. For instance, for the risk-taker solution, the probability of not exceeding a target value of US\$500 million is equal to 77.23%, whereas this probability is gradually decreased to 34.65%, 13.86% and 5.94%, in the deterministic, risk-averse and maximum *E*[*NPV*] solutions, respectively. The maximum *E*[*NPV*] solution is a rather conservative solution that behaves better than the remaining solutions for a wide range of target values on the *NPV*. In fact, there are only 3 solutions out of 72 with lower probabilities of small target values than the maximum expected *NPV* one. Note that the better performance shown by the risk-averse and risk-taker solutions in the lower and upper parts of the prob-

**Table 4 – Minimum and maximum production capacities of each technology (ton of main product per year).**

| | Technologies | | | | |
|---|---|---|---|---|---|
| | T1 | T2 | T3 | T4 | T5 |
| Minimum production capacity | 30,000 | 30,000 | 10,000 | 10,000 | 10,000 |
| Maximum production capacity | 350,000 | 350,000 | 300,000 | 300,000 | 300,000 |

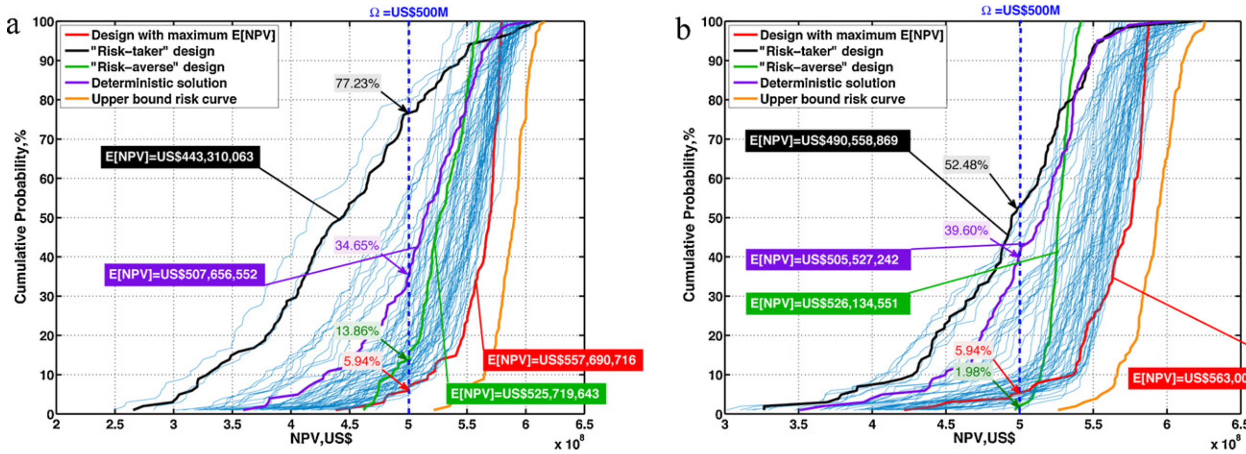


**Fig. 7 – (a) Cumulative probability curves for the case of high variance in ethanol demand. (b) Cumulative probability curves for the case of high variance in sugar demand.**

ability curves, respectively, is achieved at the expense of a big drop in the expected *NPV*. Particularly, the risk-taker and risk-averse SCs show expected *NPV*s of US$443,310,063, and US$525,719,643, whereas the maximum expected *NPV* is US$557,690,716. In between the risk-taker and risk-averse solution, we can find many SC alternatives behaving in different ways in the face of uncertainty. From these solutions, decision-makers must choose the best one according to their preferences.

Tables 8 and 9 present the structure of the SC associated with the deterministic solution. The design decisions include the construction of 4 sugar mills utilizing technology T2, and 4 distilleries operating with technologies T4 and T5. The production facilities are situated exclusively at the sub-regions of Tucumán and the North West region. 254 medium trucks for sugars and 157 tank trucks for ethanol are purchased to transport the final products from Tucumán and the North West region to the remaining sub-regions. The storages for solid materials (i.e., the ones utilizing technology S1) are present in all sub-regions. Storage facilities for ethanol (i.e., warehouses with technology S2), exist only in 4 sub-regions with comparatively large ethanol demand.

Tables 10, 11 and 12 summarize the SC configurations of the risk-taker, risk-averse and maximum *E*[*NPV*] solutions, respectively. As shown, the risk-taker configuration shows larger production and transport capacities than the risk-averse and maximum *E*[*NPV*] designs. On the other hand, it leads to fewer storage facilities. The overall capital expenditures of the risk-averse network are lower than those associated with the remaining solutions, mainly because the extra investment in production plants and transport units is compensated by the savings in storage facilities.

**Table 7 – Parameters used to calculate the capital and operating cost for different transportation modes.**

| | Heavy truck | Medium truck | Tanker truck |
|---|---|---|---|
| Average speed (km/h) | 55 | 60 | 65 |
| Capacity (ton per trip) | 65 | 25 | 28 |
| Availability of transportation mode (h/d) | 18 | 18 | 18 |
| Cost of establishing transportation mode (US$) | 90,000 | 65,000 | 100,000 |
| Driver wage (US$/h) | 10 | 10 | 10 |
| Fuel economy (km/L) | 5 | 5 | 5 |
| Fuel price (US$/L) | 0.85 | 0.85 | 0.85 |
| General expenses (US$/d) | 8.22 | 8.22 | 8.22 |
| Load/unload time of product (h/trip) | 6 | 6 | 6 |
| Maintenance expenses (US$/km) | 0.0976 | 0.0976 | 0.0976 |

**Table 8 – Production capacity in the deterministic solution.**

| Technology | Main product | Number of plants | Sub-region | Capacity, ton of main product/year | Total capacity of main product, ton/year |
|---|---|---|---|---|---|
| Deterministic solution: US$1,423,561,900 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 171,958 | |
| T2 | White sugar | 3 | Tucumán | 828,042 | 1,000,000 |
| T4 | Ethanol | 1 | North West | 38,498 | |
| T4 | Ethanol | 1 | Tucumán | 185,383 | |
| T5 | Ethanol | 1 | North West | 272,922 | |
| T5 | Ethanol | 1 | Tucumán | 230,116 | 726,918 |

**Table 9 – Storage capacity in the deterministic solution, ton.**

| Type | Córdoba | Mesopotamia | Buenos Aires | Cuyo | North | North West | Tucumán | Santa Fe | La Pampa | Santiago | West | Patagonia | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| S1 | 4610 | 4610 | 24,980 | 3951 | 2190 | 2623 | 2036 | 4445 | 461 | 1191 | 1004 | 2694 | 54,795 |
| S2 | 5071 | 5071 | 26,804 | 0 | 0 | 2885 | 0 | 0 | 0 | 0 | 0 | 0 | 39,831 |

Note that the aforementioned capacities are first-stage variables that limit the potential production rates and storage inventories. According to the demand that finally materializes, the SC can rearrange the materials flows in order to take full advantage of the production and storage capacities. Hence, larger production, transport and storage facilities make it easier to follow a given demand pattern.

Table 13 presents the risk metrics calculated for the different designs. As compared with the risk-taker design, the risk-averse solution offers the maximum reduction in *VaR* from a value of US$137M to US$53M (i.e., a 61.3% reduction). As regards the *OV*, the greatest decrease in this measure can be observed in the solution with the maximum *E*[*NPV*]. Particularly, it reduces the *OV* from a value of US$122M to US$21M (i.e., a 83% reduction). In order to calculate the *RAR*, the risk-taker solution has been chosen as the reference design. As shown, all solution have values of *RAR* much less than 1, and the corresponding cumulative risk curves are positioned almost below the risk-taker one. The risk-averse solution has the greatest value of *RAR* (equal to 0.3). This means that for the risk-averse, maximum *E*[*NPV*] and deterministic solutions the gain in risk reduction is higher than the loss in opportunity.

Figs. 8a, 9a, 10a show the cumulative probability curves of the demand satisfaction levels of white sugar, raw sugar and ethanol, respectively. That is, for a given target on the demand satisfaction level (*x* axis), these figures provide the probability (*y* axis) of achieving a demand satisfaction level less than or equal to that particular target. These curves have been determined for each SC configuration from the sales and demand of sugar and ethanol in each scenario realization. The numbers on these plots show the expected values of the corresponding cumulative probability distributions.

As observed, the curves for white and raw sugar demand satisfaction are rather similar in all the cases (i.e., the expected values do not differ in more than 1.5%). This is because the variability associated with the sugar demand is very low, and all the SC configurations are capable of fulfilling it to a large extent in all the scenarios. In contrast, the ethanol demand satisfaction curves are rather different (expected values in the range 42.1% to 74.5%). The risk-taker SC attains the lowest expected value of ethanol demand satisfaction. This is due to the establishment of only two ethanol storages that allow to cover the demand of only two regions of the country. On the other hand, the design with maximum *E*[*NPV*] leads to the largest ethanol demand satisfaction level. These curves shed light on the performance of each SC configuration under uncertainty. Particularly, the maximum expected *NPV* solution shows better performance in a wide range of *NPV* values due to the establishment of more storage facilities that allow to fulfill the ethanol demand to a larger extent. In contrast, the risk-taker solution invests on fewer storage facilities in order to reduce the capital cost. This leads to larger benefits in scenarios with low demand, but also to poor *NPV*s when large demands are materialized.

Comparing the solutions generated by the SAA with the deterministic one, it is observed that there are 60 out of 72 SC configurations that yield better performance than the deterministic design. Furthermore, the expected *NPV* in the deterministic case is US$50,034,164 lower than that attained by the maximum expected *NPV* solution identified by the SAA. With regard to the shape of the risk curves, the deterministic solution leads to a risk-averse probability curve.

**Table 10 – Production capacities for risk-taker, risk-averse and maximum *E*[*NPV*] solutions for the case of high variance in ethanol demand.**

| Technology | Main product | Number of plants | Sub-region | Capacity, ton of main product/year | Total capacity of main product, ton/year |
|---|---|---|---|---|---|
| Risk-taker solution: US$1,388,582,700 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 174,777 | |
| T2 | White sugar | 3 | Tucumán | 813,576 | 988,354 |
| T4 | Ethanol | 1 | North West | 39,129 | |
| T4 | Ethanol | 1 | Tucumán | 182,144 | |
| T5 | Ethanol | 1 | North West | 271,275 | |
| T5 | Ethanol | 1 | Tucumán | 236,565 | 731,113 |
| Risk-averse solution: US$1,498,569,200 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 286,477 | |
| T2 | White sugar | 2 | Tucumán | 700,000 | 986,477 |
| T4 | Ethanol | 1 | North West | 64,137 | |
| T4 | Ethanol | 1 | Tucumán | 156,716 | |
| T5 | Ethanol | 1 | North West | 206,030 | |
| T5 | Ethanol | 1 | Tucumán | 300,000 | 726,883 |
| Maximum *E*[*NPV*] solution: US$1,457,363,600 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 282,176 | |
| T2 | White sugar | 2 | Tucumán | 700,000 | 982,176 |
| T4 | Ethanol | 1 | North West | 63,174 | |
| T4 | Ethanol | 1 | Tucumán | 156,716 | |
| T5 | Ethanol | 1 | North West | 208,621 | |
| T5 | Ethanol | 1 | Tucumán | 300,000 | 728,511 |

**Table 11 – Storage capacities for risk-taker, risk-averse and maximum *E*[*NPV*] solutions for the case of high variance in ethanol demand, ton.**

| Type | Córdoba | Mesopotamia | Buenos Aires | Cuyo | North | North West | Tucumán | Santa Fe | La Pampa | Santiago | West | Patagonia | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk-taker solution | | | | | | | | | | | | | |
| S1 | 4838 | 5080 | 24,304 | 4388 | 2386 | 2876 | 2094 | 4566 | 465 | 1225 | 1027 | 2710 | 55,959 |
| S2 | 0 | 4910 | 36,093 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 41,003 |
| Risk-averse solution | | | | | | | | | | | | | |
| S1 | 4686 | 4983 | 25,107 | 4058 | 2154 | 2816 | 2231 | 4551 | 495 | 1272 | 1072 | 2797 | 56,224 |
| S2 | 6909 | 4754 | 12,605 | 5350 | 0 | 3970 | 2838 | 6032 | 0 | 0 | 0 | 4085 | 46,543 |
| Maximum *E*[*NPV*] solution | | | | | | | | | | | | | |
| S1 | 4537 | 4688 | 25,867 | 3867 | 2214 | 2707 | 2116 | 4717 | 487 | 1254 | 993 | 2848 | 56,295 |
| S2 | 5776 | 5129 | 22,048 | 3582 | 0 | 3821 | 0 | 4250 | 0 | 0 | 0 | 0 | 44,605 |

### 5.2. *High variance in sugar demand*

In this case, we assume a standard deviation equal to 30% for white and raw sugars demands and 5% for ethanol demand. The resulting non-dominant cumulative risk curves are presented in Fig. 7b. As compared to the case of high variance in ethanol demand, the resulting values of *NPV* under high variance in sugar demand show a narrower interval that goes from US$301 to US$626 million. The risk of not exceeding the target of $500 million in the risk-taker solution is equal to 52.48%. In the deterministic, the maximum *E*[*NPV*], and the risk-averse solutions these probabilities are equal to 39.60%, 5.94%, 1.98%, respectively. As happened previously, the solution with the maximum *E*[*NPV*] behaves quite conservatively, and there are only 12 out of 68 non-dominant solutions with lower probabilities of small target values than the maximum expected *NPV* one.

**Table 12 – Number of transportation vehicles for risk-taker, risk-averse and maximum *E*[*NPV*] solutions for the case of high variance in ethanol demand.**

| Design | Heavy truck | Medium truck | Tank truck |
|---|---|---|---|
| Risk-taker | 0 | 248 | 187 |
| Risk-averse | 0 | 255 | 142 |
| Maximal *E*[*NPV*] | 0 | 257 | 151 |

Tables 14, 15 and 16 present the resulting first-stage variables of the SC configurations obtained for the risk-taker, risk-averse and maximum *E*[*NPV*] solutions. As observed, all the networks involve highly centralized organizations with a tendency to build the sugar mills and the distilleries in the sub-regions with their own sugar cane plantations. Particulary, the model decides to install production facilities only in the sub-regions with large sugar cane capacities namely Tucumán and North West.

Regarding storage, all the configurations have storages for sugars. Thereby, the main factor causing different shapes and slopes of the risk curves in the case of high variance in sugar demand is the sugar production capacity. As shown, the risk-

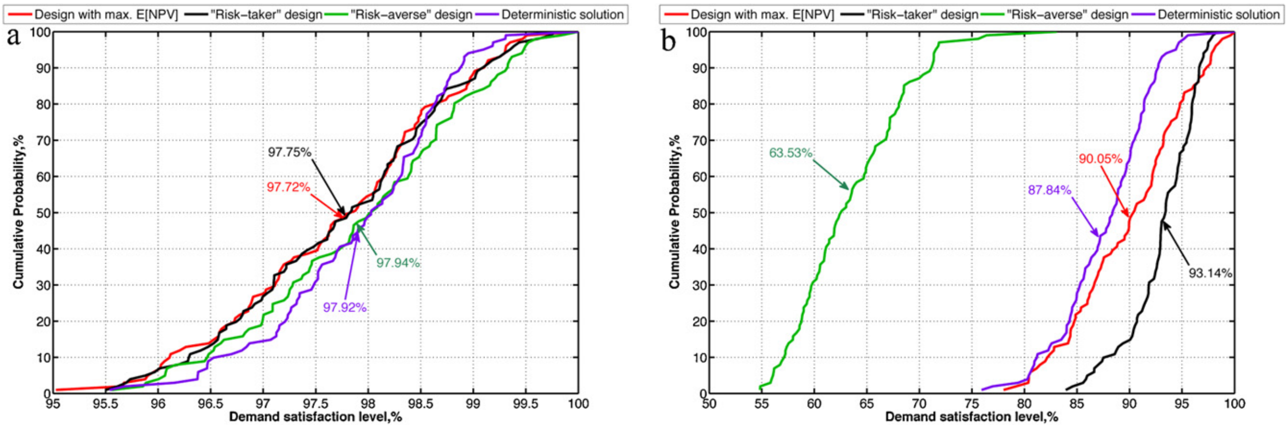


**Fig. 8 – (a) Cumulative probability curves for white sugar demand satisfaction level under high variance in ethanol demand. (b) Cumulative probability curves for white sugar demand satisfaction level under high variance in sugar demand.**

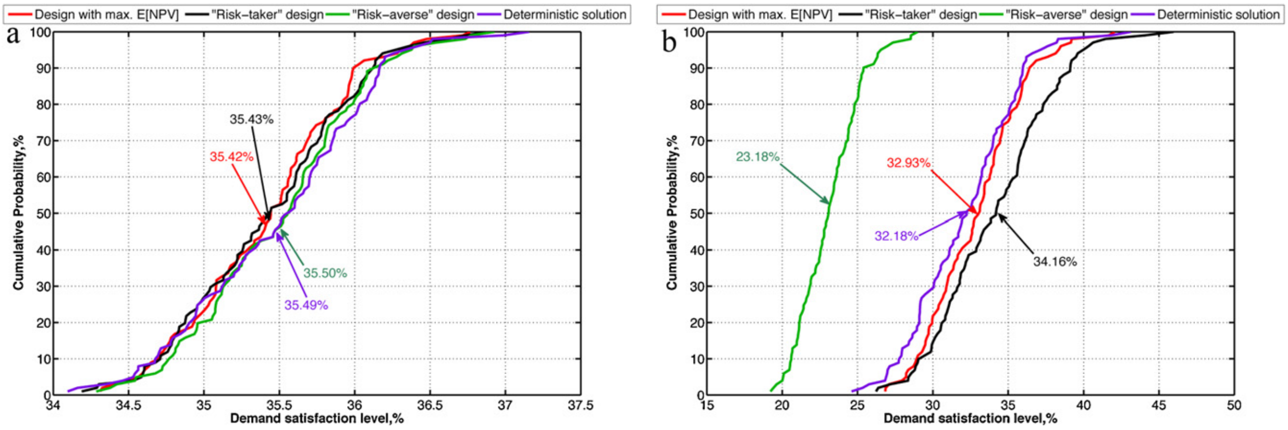


**Fig. 9 – (a) Cumulative probability curves for raw sugar demand satisfaction level under high variance in ethanol demand. (b) Cumulative probability curves for raw sugar demand satisfaction level under high variance in sugar demand.**

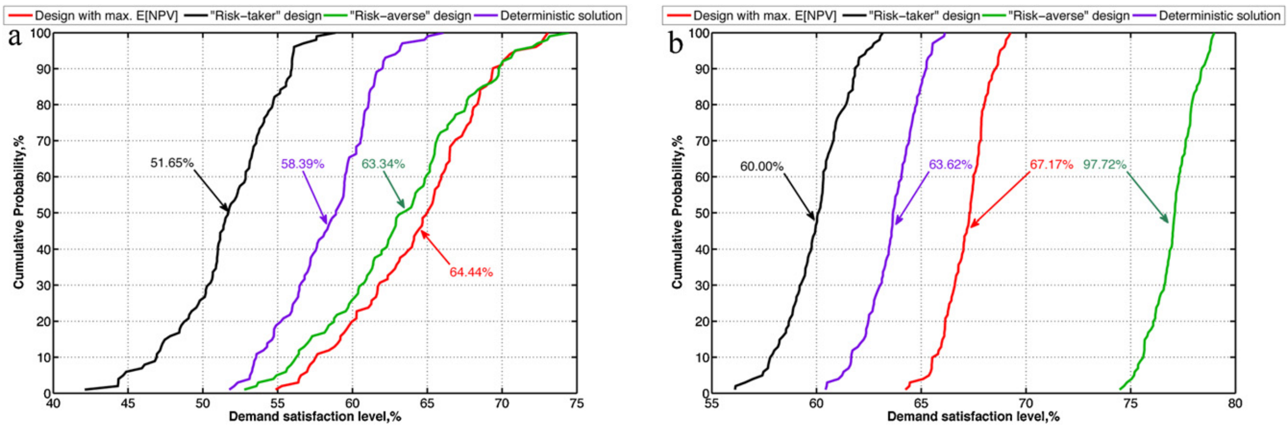


**Fig. 10 – (a) Cumulative probability curves for ethanol demand satisfaction level under high variance in ethanol demand. (b) Cumulative probability curves for ethanol demand satisfaction level under high variance in sugar demand.**

**Table 13 – Values of *VaR*, *OV* and *RAR* to risk-taker design for the selected solutions, US$.**

| | Type of solution | | | |
|---|---|---|---|---|
| | Risk-taker | Risk-averse | Maximum *E*[NPV] | Deterministic |
| High variance in ethanol demand | | | | |
| *VaR* | 138,615,053 | 52,530,213 | 75,025,076 | 101,789,033 |
| *OV* | 121,911,937 | 32,622,837 | 20,945,374 | 62,400,497 |
| RAR | – | 0.30 | 0.09 | 0.17 |
| High variance in sugar demand | | | | |
| *VaR* | 111,538,469 | 16,744,581 | 68,545,708 | 98,746,232 |
| *OV* | 65,834,581 | 12,203,389 | 23,312,212 | 47,085,358 |
| RAR | – | 0.17 | 0.01 | 0.10 |

**Table 14 – Production capacities for risk-taker, risk-averse and maximum *E[NPV]* solutions for the case of high variance in white and raw sugars demand.**

| Technology | Main product | Number of plants | Sub-region | Capacity, ton of main product/year | Total capacity of main product, ton/year |
|---|---|---|---|---|---|
| Risk-taker solution: US$1,440,257,000 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 204,605 | |
| T2 | White sugar | 3 | Tucumán | 886,013 | 1,090,618 |
| T4 | Ethanol | 1 | North West | 45,807 | |
| T4 | Ethanol | 1 | Tucumán | 198,361 | |
| T5 | Ethanol | 1 | North West | 253,852 | |
| T5 | Ethanol | 1 | Tucumán | 196,254 | 694,275 |
| Risk-averse solution: US$1,406,887,800 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 301,103 | |
| T2 | White sugar | 1 | Tucumán | 350,000 | 651,103 |
| T4 | Ethanol | 1 | North West | 67,411 | |
| T4 | Ethanol | 1 | Tucumán | 78,358 | |
| T5 | Ethanol | 1 | North West | 197,487 | |
| T5 | Ethanol | 2 | Tucumán | 509,346 | 852,602 |
| Maximum *E[NPV]* solution: US$1,415,866,400 of capital investments | | | | | |
| T2 | White sugar | 1 | North West | 232,327 | |
| T2 | White sugar | 2 | Tucumán | 700,000 | 932,327 |
| T4 | Ethanol | 1 | North West | 52,013 | |
| T4 | Ethanol | 1 | Tucumán | 156,716 | |
| T5 | Ethanol | 1 | North West | 237,660 | |
| T5 | Ethanol | 1 | Tucumán | 300,000 | 746,390 |

**Table 15 – Storage capacities for risk-taker, risk-averse and maximum *E[NPV]* solutions at the case of high variance in white and raw sugars demand, ton.**

| Type | Córdoba | Mesopotamia | Buenos Aires | Cuyo | North | North West | Tucumán | Santa Fe | La Pampa | Santiago | West | Patagonia | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk-taker solution | | | | | | | | | | | | | |
| S1 | 7000 | 5803 | 28,314 | 6961 | 3179 | 3641 | 3067 | 6418 | 606 | 1107 | 1443 | 2088 | 69,628 |
| S2 | 5159 | 5082 | 25,368 | 0 | 0 | 3069 | 0 | 0 | 0 | 0 | 0 | 0 | 38,678 |
| Risk-averse solution | | | | | | | | | | | | | |
| S1 | 6347 | 4426 | 10,677 | 6315 | 2379 | 3059 | 2509 | 6320 | 452 | 1538 | 1350 | 3167 | 48,539 |
| S2 | 5127 | 5002 | 24,898 | 4208 | 0 | 3048 | 0 | 4972 | 0 | 0 | 0 | 0 | 47,254 |
| Maximum *E[NPV]* solution | | | | | | | | | | | | | |
| S1 | 5779 | 5401 | 58,772 | 4947 | 2528 | 9650 | 2636 | 4979 | 568 | 1444 | 1227 | 34,947 | 132,879 |
| S2 | 5151 | 5065 | 26,786 | 0 | 0 | 0 | 0 | 5040 | 0 | 0 | 0 | 0 | 42,042 |

**Table 16 – Number of transportation vehicles for risk-taker, risk-averse and maximum *E[NPV]* solutions for the case of high variance in sugar demand.**

| Design | Heavy truck | Medium truck | Tank truck |
|---|---|---|---|
| Risk-taker | 0 | 281 | 149 |
| Risk-averse | 0 | 162 | 175 |
| Maximal *E[NPV]* | 0 | 239 | 171 |

taker solution has the largest production capacity of white and raw sugar and the lowest ethanol production capacity. In contrast, the configuration from the risk-averse solution is ethanol-oriented. The probability curves for white sugar, raw sugar and ethanol demand satisfaction levels are shown in Figs. 8b, 9b and 10b, respectively. As observed, the risk-taker design attains the highest expected demand satisfaction of white and raw sugar, whereas the risk-averse configuration shows the largest ethanol demand satisfaction level.

Comparing the solutions generated by the SAA algorithm with the deterministic one, we see that there are 60 out of 68 SC configurations that yield better performance than the deterministic design. Furthermore, the expected *NPV* in the deterministic case is US$57,474,176 lower than that attained by the maximum expected *NPV* solution identified by the SAA. Regarding the shape of the risk curves, the deterministic solution results in a risk-taker probability curve.

As regards the risk metrics, the risk-averse solution leads to the largest decrease in both *VaR* and *OV* values (see Table 13). Particularly, It reduces the value at risk from US$112M to US$17M (85% reduction). The value of *OV* is decreased from US$67M to US$12M (82% reduction). In addition, the risk area for this solution is the largest one (i.e., 0.17).

## 6. Conclusions

In this work, we have proposed a two-stage stochastic mixed-integer linear programming approach for the optimal design and planning of bioethanol SCs under uncertainty in product demand. The problem was solved applying the SAA algorithm, which provides as output a set of SC configurations that behave in different ways in the face of uncertainty.

A real case study based on the current Argentinean sugar cane industry has been presented to show the capabilities of our approach. Since the final products of the sugar cane industry in Argentina are sugar and bioethanol, we developed two different case studies that differ in the variance of the uncertain sugar and ethanol demands. Numerical results show that the centralized production is more favorable. Furthermore, the production facilities should be located close to the sugar cane plantations. Among the technologies that convert sugar cane to white and raw sugars the one producing honey as a by-product is preferable. In addition, it is concluded that ethanol should be produced by fermentation of sugarcane juice or honey from sugar mills.

We have shown that the SAA is able to provide solutions that behave better than the deterministic one in the face of uncertainty (i.e., solutions yielding better expected *NPV* than that associated with the deterministic one). The proposed methodology offers different risk-related alternatives for decision-making. The analysis of the stochastic results reveals that there are two critical factors that influence the SC performance under uncertainty. The first one is the production capacity. As a rule, risk-taker SC configurations imply production facilities with larger capacities. The second one is the amount of storages and transportation units. SCs with larger number of warehouses and trucks provide more flexibility to rearrange products flows, which makes it easier to implement risk-averse manufacturing policies. These configurations, however, require larger capital investments and therefore lead to lower profits. The tool presented in this work is intended to help policy makers in the strategic planning of infrastructures for ethanol and sugar production in the face of uncertainity.

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## Appendix A. Supplementary Data

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.cherd.2011.07.013.

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