

Integrating pricing policies in the strategic planning of supply chains: a case study of the sugar cane industry in Argentina

Andrey M. Kostin^a, Gonzalo Guillén-Gosálbez^{a*}, Fernando D. Mele^b, Miguel J. Bagajewicz^c, Laureano Jiménez^a

^a*Universitat Rovira i Virgili, Av. Països Catalans 26, Tarragona 43007, Spain,
gonzalo.guillen@urv.cat, laureano.jimenez@urv.cat*

^b*Universidad Nacional de Tucumán, Av. Independencia 1800, S. M. de Tucumán
T4002BLR, Argentina, fmele@herrera.unt.edu.ar*

^c*School of Chemical, Biological and Material Engineering, University of Oklahoma,
Norman, Oklahoma, 73019, USA, bagajewicz@ou.edu*

Abstract

In this paper, we address the strategic planning of supply chains for ethanol and sugar production under uncertainty in the market trends. The design task is formulated as a mixed-integer linear programming (MILP) problem that decides on the capacity expansions of production and storage facilities over time along with the associated sales decisions. The main novelty of the work lies in the incorporation of a price-demand relationship explicitly at the modeling stage. Thus, prices are regarded in our work as decision variables, whereas the demand is determined based on the prices calculated by the model. To incorporate the trade-off between the expected profit and risk that naturally exists in an uncertain environment of this type, we employ the sample average approximation (SAA) algorithm. The capabilities and possibilities of this approach are demonstrated through case studies based on Argentinean sugar cane industry.

Keywords: Optimization; pricing policies, bioethanol, supply chain, sugar cane; financial risk

1. Introduction

The production of plant-based fuels has recently gained wider interest given their potential to reduce both the consumption of crude oil and the associated environmental impact. Specifically, bioethanol is currently among the most important biofuels in terms of its production rate, which has risen from 13,100 millions of gallons in 2007 to 17,300 millions of gallons in 2008 [1]. This rapid development has been motivated by several advantages of the bioethanol compared to other liquid fuels. Particularly, the octane number (*i.e.*, 99) is higher than the average octane number of gasoline. On the other hand, pure ethanol shows a lower heating value: 21 MJ/L for ethanol versus 30 MJ/L for gasoline. However, by blending it in low proportion with gasoline, it becomes suitable for common internal combustion engines without any significant changes in engine performance and construction [2].

Argentina has great potential to produce bioethanol. It has abundant natural resources, a very efficient agricultural production sector, and the domestic sugar industry has a strong structure, having increased efficiency and production significantly in the last years. In 2007 the Argentine Government published Law 26,093 on biofuels. It forces the use of biofuels by 2010 with an obligatory mix of 5 percent of ethanol in gasoline

and 5 percent of biodiesel in diesel. To comply with it, private analysts forecast that a volume of 250 million L/year of ethanol will be needed [3].

The circumstances open a big challenge for the sugar cane industry: the opportunity to divert part of the cane from sugar into ethanol production, providing mills more flexibility in their production mix, and increasing overall operational efficiency. This flexibility is intricately related to internal and external products prices and demand, and subsidy measures.

The aim of this paper is to provide a decision-support tool for the optimal strategic planning of supply chains (SCs) for ethanol production. The main novelty of our work is the development of a mathematical formulation that integrates all the components of the ethanol SC into a single framework in order to optimize strategic SC decisions. The model presented in this paper allows to determine in a systematic way the capacity expansions of the production and storage facilities of the network over time as well as the associated planning decisions.

2. Problem statement

The proposed model has to determine the structure of the three-echelon SC (production-storage-market). This network includes a set of plants and a set of storage facilities, where products are stored before being delivered to the final customers. The facilities can be installed in a set of regions or grids that correspond to the potential locations in which the overall regions of interest is divided. The problem addressed in this paper can be formally stated as follows:

Given are a fixed time horizon (T), a set of possible product prices (PR_{igte}) and corresponding demands (D_{ikte}), cost parameters for production (UPC_{ipgt}), storage (USC_{isgt}) and transportation of materials (FP_{lt} , FE_l , DW_{lt} , GE_{lt} , $TCap_l$, EL_{gg} , SP_l), taxes rate (ϕ), minimum and maximum capacity of plants (τ , $PCap^{min}_p$, $PCap^{max}_p$, $PCapE^{min}_p$, $PCapE^{max}_p$), storages ($SCap^{min}_s$, $SCap^{max}_s$, $SCapE^{min}_s$, $SCapE^{max}_s$) and transportation links (Q^{max}_l , Q^{min}_l), capital cost data (α^{PL}_{pgt} , β^{PL}_{pgt} , α^S_{sgt} , β^S_{sgt}), interest rate for NPV calculations (ir), landfill tax (LT_{ig}) and upper limit for capital investment (UCI).

The goal is to determine the configuration of the bioethanol network and the associated planning decisions with the goal of maximizing the expected net present value ($E[NPV]$). The model determines the number, location, capacity of production plants and warehouses to be set up in each grid, their capacity expansion policy, the transportation links and transportation modes that need to be established in the network, the production rates and flows of feed stocks, wastes and final products, as well as the prices of final products and demands over the planning horizon.

3. Pricing model

In microeconomics, one way to obtain the demand function is to solve a consumer utility-maximization problem limited by a consumer budget (Y) and a maximum possible demand D . Taking into account the two products with demands d_1 (for our product) and d_2 (for competitor's product), we maximize the utility function $U(d_1, d_2)$ subject to a budget limitation and a total demand limitation:

$$\begin{aligned} \max \quad & U(d_1, d_2) \\ \text{s.t.} \quad & p_1 d_1 + p_2 d_2 \leq Y \leq D \end{aligned} \tag{1}$$

where p_1 is our price, and p_2 is a competitor's price. In this work, we use a constant elasticity of substitution (CES) utility function:

$$U(d_1, d_2) = (x_1^\rho + x_2^\rho)^{1/\rho} \quad (2)$$

In Eq.(2), x is a satisfaction function, which has the following forms:

$$x_1 = \alpha d_1, \quad x_2 = \beta d_2 \quad (3)$$

where β is a measure of how much a consumer prefers our product to product 2, and α is a measure of how much the consumer population is aware of the quality of our product. When the consumer budget is binding, the solution of the problem 1 [4, 5] is:

$$p_1 d_1^{1-\rho} = \left(\frac{\alpha}{\beta}\right)^\rho p_2 \left[\frac{Y - p_1 d_1}{p_2} \right] \quad (4)$$

Several parameters of the previous equation, namely α , β and ρ , were determined based on historical data on sugar and ethanol sales. The competitor's price is assumed to be constant and equal to the current market price. Regarding our price, the model is free to choose from a set of k possible prices (PR_{igte}). This condition is valid only for sugar, due to the fact, that ethanol price in Argentina is regulated by government and in a medium-range planning problem can be considered as fixed. The uncertainty is introduced in the consumer budget (Y_e). Thereby, the solution of Eq. (4) provides product demand (d_{ietk}) for each randomly generated consumer budget and corresponding price PR_{igte} . Due to the nonlinear nature of the price-demand relationship, Eq. (4) was solved separately in Matlab®, and the obtained demands for the discrete sizes were then regarded as parameters in the optimization model.

4. Stochastic formulation

As previously mentioned, the uncertainty is introduced through the demand and sugar prices. Two models were developed: a “general” planning problem without price-demand relationship and an “advanced” planning problem with the incorporation of the price-demand relationship. For both formulations, the stochastic results are obtained using a sample average approximation (SAA) algorithm [6]. Following this approach, a full deterministic model is solved for each scenario, and then the design variables (the number of production and storage facilities, their expansion policies within planning horizon and the number of transportation units) are fixed and the model is run again for the remaining scenarios. After that, non-dominated risk curves are selected and analyzed.

5. Mathematical model

The MILP formulation is based on that introduced by Almansoori and Shah [7] and Guillén-Gosálbez *et al.* [8] for the case of hydrogen SCs and Guillén-Gosálbez and Grossmann for the case of petrochemical SCs [9]. It includes integer variables representing the number of plants (NP_{pgt}) and storage facilities (NS_{sgt}) established in each potential location and time period, as well as transportation units (NT_{it}) circulating between the SC entities. On the other hand, binary variables are used to represent the establishment of transportation links between grids in each time period ($X_{lgg'ie}$) and to choose one optimal price from the set of possible prices (YP_{ikte}), whereas continuous ones denote the transportation flows, capacity expansions, storage inventories and production rates.

The model includes three main blocks of equations: mass balances, capacity constraints and objective function. A brief outline of each of these sets of equations is next given.

5.1. Mass balance equations

Overall mass balance for each grid zone in scenario e is represented by Eq.(5). In accordance with it, for every material form i , the initial inventory kept in grid g ($ST_{isgt-le}$) plus the amount produced (PT_{igte}) the amount of raw materials purchased (PU_{igte}) and the input flow rate ($Q_{ilg'gte}$) must equal the final inventory (ST_{isgte}) plus the amount delivered to customers (DTS_{igte}) plus the output flow ($Q_{ilgg'te}$) and the amount of waste generated (W_{igte}):

$$\sum_{s \in SI(i,s)} ST_{isgt-le} + PT_{igte} + PU_{igte} + \sum_l \sum_{g' \neq g} Q_{ilg'gte} = \sum_{s \in SI(i,s)} ST_{isgte} + DTS_{igte} + \sum_l \sum_{g \neq g'} Q_{ilgg'te} + W_{igte} \quad \forall i, g, t, e \quad (5)$$

5.2. Capacity constraints

Production and storage capacity expansions are bounded between upper and lower limits:

$$NP_{pgt} PCap_p^{\min} \leq PCapE_{pgt} \leq NP_{pgt} PCap_p^{\max} \quad \forall p, g, t \quad (6)$$

$$NS_{sgt} SCap_s^{\min} \leq SCapE_{sgt} \leq NS_{sgt} SCap_s^{\max} \quad \forall s, g, t \quad (7)$$

The material flow in scenario e is constrained by the minimum and maximum allowable transportation capacity:

$$Q_l^{\min} X_{lg'gte} \leq \sum_{i \in IL(i,l)} Q_{ilg'gte} \leq Q_l^{\max} X_{lg'gte} \quad \forall l, g, g', t, e \quad (8)$$

The production rate of sugar cane ($PT_{l,igte}$) in each scenario e is limited by the available capacities of sugar cane plantations situated in grid g in time t ($CapCrop_g$):

$$PT_{igte} \leq CapCrop_g \quad \forall i = 1, g, t, e \quad (9)$$

5.3. Objective function

At the end of the time horizon, a different value of NPV_e is obtained for each realization of demand uncertainty for the selected price. The proposed model must account to the maximization of the expected value ($E[NPV]$) of the resulting NPV_e distribution:

$$E[NPV] = \sum_e prob_e NPV_e \quad (10)$$

The NPV_e can be determined from the discounted cash flows (CF_{te}) generated in each of the time intervals t in which the total time horizon is divided:

$$NPV_e = \sum_t \frac{CF_{te}}{(1+ir)^{t-1}} \quad \forall e \quad (11)$$

Bagajewicz [10] points out that NPV is not necessarily a good measure of profit in conditions where the capital investment is not fixed. Therefore, it is convenient to

consider the maximization of NPV subject to different maximum available capital and then check the return of investment. For brevity, we omit this step.

6. Results and discussion

All the models were written in GAMS and solved with the MILP solver CPLEX 11.0 on a HP Compaq DC5850 PC with AMD Phenom 8600B 2.29 GHz triple-core processor and 2.75 Gb of RAM.

The model contains 10 grids representing the provinces located in the north of Argentina. Only 5 of them possess sugar cane plantations, while the remaining provinces can import sugar cane, which eventually leads to an increase in the transportation operating cost. Domestic Argentinean sugar cane industry operates with 5 production technologies, 2 different storage technologies and 3 types of transportation trucks. The length of the time horizon is 4 years. The uncertainty is represented by a set of 30 scenarios that were generated from Monte Carlo sampling. The set of allowable prices contains 8 discrete values. The risk curves obtained by the “general model” are depicted in Figure 1. The thick dashed line is the solution with Maximum E[NPV]. This curve indicates a 30% risk of losing money. An inspection of the lower portion of the curve indicates the existence of non-dominated solutions that can be used to reduce risk, but at a cost of reducing the upside potential to that of the maximum E[NPV] or even lower.

The resulted risk curves of the “advanced” model are shown in Figure 2. The results indicate, that this model provides the solution with higher E[NPV] and less risk than the “general” model. Particularly, the solution with Maximum E[NPV] shows a 20% risk of losing money. Having the possibility to determine a price, the “advanced” model chooses the higher values of sugar prices than the “general” model. That leads to shrinkage in the sugar demand and construction of the SC with the less production capacity and risk of losing money.

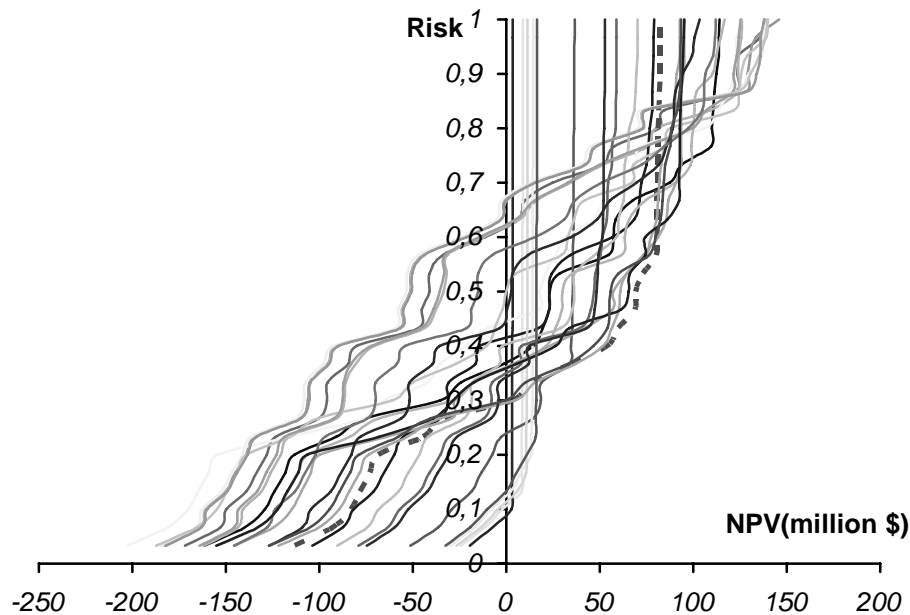


Figure1. The risk curves of the “general” planning model.

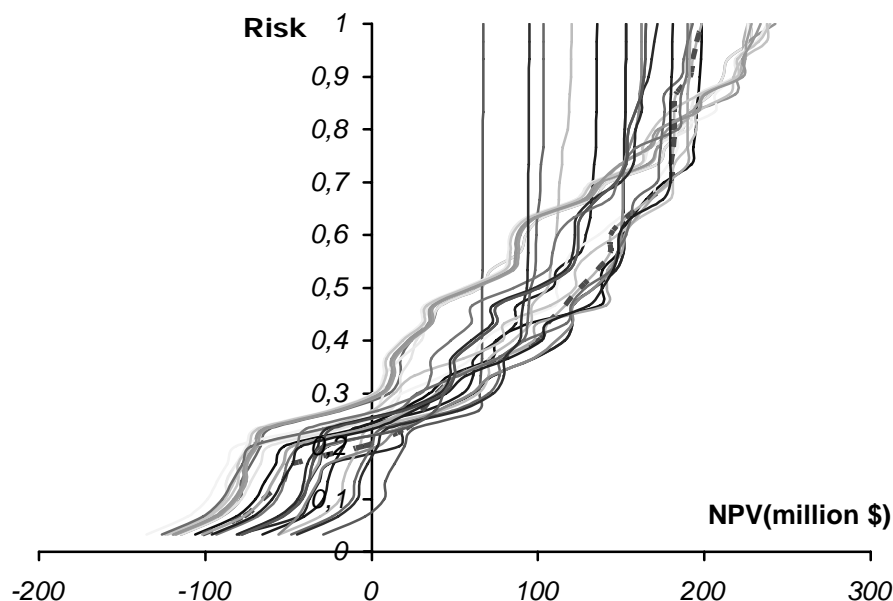


Figure 2. The risk curves of the “advanced” planning model.

7. Conclusions

In this paper, an optimization model for strategic planning of SC for ethanol production was described. The price-demand relationship was integrated into proposed model to determine the optimal price and corresponding demand for final products. The SAA algorithm was employed to consider the uncertainty in consumer budget and generate the risk curves. After that, the results generated by the model with pricing decision and the general model with fixed prices were compared. The results shown, that the “advanced” model provides the solution with higher $E[NPV]$ and less risk of losing money.

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