Computers and Chemical Engineering 35 (2011) 2540–2563

Contents lists available at ScienceDirect

Computers and Chemical Engineering

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

A novel rolling horizon strategy for the strategic planning of supply chains. Application to the sugar cane industry of Argentina

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ARTICLE INFO

Article history:
Received 10 April 2010
Received in revised form 10 January 2011
Accepted 12 April 2011
Available online 22 April 2011

Keywords:
Supply chain management (SCM)
Bioethanol
Sugar cane industry
Rolling horizon

ABSTRACT

In this article, we propose a new method to reduce the computational burden of strategic supply chain (SC) planning models that provide decision support for public policy makers. The method is based on a rolling horizon strategy where some of the integer variables in the mixed-integer programming model are treated as continuous. By comparing with rigorous solutions, we show that the strategy works efficiently. We illustrate the capabilities of the approach presented by its application to a SC design problem related to the sugar cane industry in Argentina. The case study involves determining the number and type of production and storage facilities to be built in each region of the country so that the ethanol and sugar demand is fulfilled and the economic performance is maximized.

1. Introduction

Supply chain management (SCM) has recently gained wider interest in both, academia and industry, given its potential to increase the benefits through an efficient coordination of the operations of supply, manufacturing and distribution carried out in a network (Naraharisetti, Adhitya, Karimi, & Srinivasan, 2009; Puigjaner & Guillén-Gosálbez, 2008). In the context of process systems engineering (PSE), these activities are the focus of the emerging area known as Enterprise Wide Optimization (EWO), which as opposed to SCM, places more emphasis on the manufacturing stage (Grossmann, 2005).

The SCM problem may be considered at different levels depending on the strategic, tactical, and operational variables involved in the decision-making process (Fox, Barbuceanu, & Teigen, 2000). The strategic level is based on those decisions that have a long-lasting effect on the firm. These include, among many others, the SC design problem, which addresses the optimal configuration of an entire SC network. The tactical level encompasses long- to medium-term management decisions, which are typically updated a few times every year, and include overall purchasing and production decisions, inventory policies, and transport strategies. Finally, the operational level refers to day-to-day decisions such as scheduling, lead-time quotations, routing, and lorry loading (Guillén-Gosálbez, Espuña, & Puigjaner, 2006).

In the recent past the SCM tools developed in these hierarchical levels have primarily focused on maximizing the economic performance in the private sector. By contrast, the academic literature on SCM applications for public policy makers is still quite scarce (see Preuss, 2009). The use of SCM tools in the latter area is very promising, since they can provide valuable insight into how to satisfy the population's needs in an efficient manner, thus guiding government authorities towards the adoption of the best technological alternatives to be promoted and eventually established in a given country.

The goal of this paper is to provide a general modeling framework and a solution strategy for SC design problems, with focus on the strategic level of SCM, and with special emphasis on applications found in the public sector. Particularly, given a set of available production, storage and transportation technologies that can be adopted in different regions of a country, the goal of the analysis performed is to determine the optimal SC configuration, including the type of technologies selected, the capacity expansions over time, and their optimal location, along with the associated planning decisions that maximize a given economic criterion. In this work, such a design task is formulated in mathematical terms as a mixed-integer programming problem with a specific structure that includes integer and binary variables of different nature. To

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doi:10.1016/j.compchemeng.2011.04.006

Nomenclature

Indices

i	materials
g	sub-region zones
l	transportation modes
p	manufacturing technologies
s	storage technologies
t	time periods

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
$LI(i)$	set of transportation modes l that can transport material i
SEP	set of products that can be sold
$SI(i)$	set of storage technologies that can store materials i

Parameters

α^{PL}_{pgt}	fixed investment coefficient for technology p
α^{S}_{sgt}	fixed investment coefficient for storage technology s
β	storage period
β^{PL}_{pgt}	variable investment coefficient for technology p
β^{S}_{sgt}	variable investment coefficient for storage technology s
ρ_{pi}	material balance coefficient of material i in technology p
τ	minimum desired percentage of the available installed capacity
φ	tax rate
avl_l	availability of transportation mode l
$CapCrop_{gt}$	total capacity of sugar cane plantations in sub-region g in time t
DW_{lt}	driver wage
$EL_{gg'}$	distance between g and g'
$\overline{FCI}$	upper limit for capital investment
FE_l	fuel consumption of transport mode l
FP_{lt}	fuel price
GE_{lt}	general expenses of transportation mode l
LT_{ig}	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
PR_{igt}	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_{igt}	actual demand of product i in sub-region g in time t
SP_l	average speed of transportation mode l
sv	salvage value
T	number of time intervals
$TCap_l$	capacity of transportation mode l
TMC_{lt}	cost of establishing transportation mode l in period t
UPC_{ipgt}	unit production cost
USC_{isgt}	unit storage cost

Variables

CF_t	cash flow in time t
DC_t	disposal cost in time t
DTS_{igt}	delivered amount of material i in sub-region g in period t
FC_t	fuel cost
FCI	fixed capital investment
FOC_t	facility operating cost in time t
$FTDC_t$	fraction of the total depreciable capital in time t
GC_t	general cost
LC_t	labor cost
MC_t	maintenance cost
NE_t	net earnings in time t
NP_{pgt}	number of installed plants with technology p in sub-region g in time t
NPV	net present value of SC
NS_{sgt}	number of installed storages with storage technology s in sub-region g in time t
NT_{lt}	number of transportation units l
$PCap_{pgt}$	existing capacity of technology p in sub-region g in time t
$PCapE_{pgt}$	expansion of the existing capacity of technology p in sub-region g in time t
$Q_{ilgg't}$	flow rate of material i transported by mode l from sub-region g' to current sub-region g in time period t
Rev_t	revenue in time t
RNP_{pgt}	"relaxed" number of installed plants with technology p in sub-region g in time interval t
RNS_{sgt}	"relaxed" number of installed storages with storage technology s in sub-region g in time interval t
RNT_{lt}	"relaxed" number of transportation units l in time interval t
$SCap_{sgt}$	capacity of storage s in sub-region g in time t
$SCapE_{sgt}$	expansion of the existing capacity of storage s in sub-region g in time t
ST_{isgt}	total inventory of material i in sub-region g stored by technology s in time t
TOC_t	transport operating cost in time t
PE_{ipgt}	production rate of material i in technology p in sub-region g in time t
PT_{igt}	total production rate of material i in sub-region g in time t
PU_{igt}	purchase of material i in sub-region g in time t
$X_{lgg't}$	binary variable, which is equal to 1 if material flow between two sub-regions g and g' is established and 0 otherwise
W_{igt}	amount of wastes i generated in sub-region g in period t

expedite the solution of such formulation, we propose a novel decomposition method based on a customized "rolling horizon" algorithm that achieves significant reductions in CPU time while still providing near optimal solutions.

The paper is organized as follows. First, a literature review on strategic SCM tools based on mathematical programming is presented, followed by a more specific review on the particular application of these techniques to the sugar cane industry. A formal definition of the problem under study is given next along with its mathematical formulation. The following section introduces a tailor-made decomposition strategy that reduces the computational burden of the model by exploiting its mathematical structure. The capabilities of the proposed modeling framework and solution strategy are illustrated next through a case study based on the sugar cane industry of Argentina. The conclusions of the work are finally drawn in the last section of the paper.

1.1. Mathematical programming approaches for strategic SCM problems

Optimization using mathematical programming is probably the most widely used approach in SCM. General literature reviews can be found in the work by Mula, Peidro, Díaz-Madroñero, and Vicens (2010), whereas a more specific work devoted to process industries can be found in the articles by Grossmann (2005) and Papageorgiou (2009). The preferred modeling tool for addressing strategic SCM problems has been mixed-integer linear programming (MILP). MILP models for SCM typically adopt fairly simple aggregated representations of capacity that avoid nonlinearities. This feature has been the key of their success, since it has allowed them to be easily adapted to a wide range of industrial applications. In these MILP formulations, continuous variables are used to represent materials flows and purchases and sales of products, whereas binary variables are employed to model tactical and/or strategic decisions associated with the network configuration, such as selection of technologies and establishment of facilities and transportation links (Guillén-Gosálbez, Mele, Espuña, & Puigjaner, 2006; Laínez, Guillén-Gosálbez, Badell, Espuña, & Puigjaner, 2007).

Several solution strategies have been explored for effectively solving these strategic SCM problems. Bok, Grossmann, and Park (2000) reported an implementation of a bi-level decomposition algorithm to solve a MILP model that maximized the profit of a network showing that this algorithm could reduce the solution time by half compared to the full space method implemented in CPLEX. Guillén-Gosálbez, Mele, and Grossmann (2010) presented also a bi-level algorithm for solving the strategic planning of hydrogen SCs for vehicle use. Using numerical examples, they showed that the decomposition method could achieve a reduction of one order of magnitude in CPU time compared to the full space method (the whole model without decomposition, relaxation or approximations) while still providing near optimal solutions (i.e., with less than 1% of optimality gap).

Lagrangean decomposition has also been used in strategic SCM problems. Gupta and Maranas (1999) applied Lagrangean decomposition to solve a planning problem that considered different products and manufacturing sites. With this decomposition technique, the authors obtained a solution with an optimality gap of 1.6%, reducing in one order of magnitude the CPU time required by CPLEX 4.0 to find a solution with a gap of 3.2%. You and Grossmann (2010) introduced a spatial decomposition algorithm based on the integration of Lagrangean relaxation and piecewise linear approximation to reduce the computational expense of solving multi-echelon supply chain design problems in the presence of uncertain customer demands. Chen and Pinto (2008) investigated the application of various Lagrangean-based techniques including Lagrangean decomposition, Lagrangean relaxation, and Lagrangean/surrogate relaxation, coupled with subgradient and modified subgradient optimization. The comparison showed that the proposed strategies are much more efficient than the full space method. Particularly, they concluded that the computational time was greatly reduced while still achieving optimality gaps of less than 2%.

Other solution methods applied to SCM problems have been Bender's decomposition (Geoffrion & Graves, 1974) and "rolling horizon" algorithms based on the original work by Wilkinson (1996). The former approach has been mainly used in the context of strategic/tactical SCM problems (Cordeau, Pasin, & Solomon, 2006; Dogan & Goetschalckx, 1999; MirHassani, Lucas, Mitra, Messina, & Poojari, 2000; Paquet, Martel, & Desaulniers, 2004; Santoso, Ahmed, Goetschalckx, & Shapiro, 2005; Uster, Easwaran, Akcali, & Cetinkaya, 2007), whereas the latter strategy has been typically applied to operational SCM problems (Dimitriadis, Shah, & Pantelides, 1997; Elkamel & Mohindra, 1999; Balasubramanian & Grossmann, 2004). Rolling horizon algorithms are based on approximating the solution of the full space model by a set of sub-models, each of which representing only part of the planning horizon in detail. This strategy has been shown to be very efficient in solving scheduling problems with large time horizons (Van den Heever & Grossmann, 2003). However, to our knowledge, it has never been applied to strategic SCM problems.

1.2. Applications of mathematical programming to the sugar cane industry

The interest in renewable fuels such as bioethanol and other bio-fuels has greatly increased in the last years all over the world. Following this trend, Argentina approved the National Act 26,093, which aims to promote the production of bioethanol for fuel blending. This new legislation represents a major challenge for the sugar cane industry, which must increase its flexibility and efficiency in order to satisfy the growing sugar and bioethanol demand. The final goal of this law is to promote the adoption of proper energetic and environmental policies.

The interest on ethanol has motivated the development of mathematical programming tools for optimizing its production. The models presented so far have mainly focused on studying the individual components of the ethanol SC rather than optimizing all its entities in an integrated manner. Particularly, Yoshizaki, Muscat, and Biazzi (1996) introduced a LP model to find the optimal distribution of sugar cane mills, fuel bases and consumer sites in southeastern Brazil. Kawamura, Ronconi, and Yoshizaki (2006) presented a LP model to minimize the transportation and external storage costs of the existing SC in Brazil. Ioannou (2005) applied a LP optimization model to reduce the transportation cost in the Greek sugar industry, while Milán, Fernández, and Pla Aragonés (2006) introduced a MILP model to minimize the transportation cost of a sugar cane SC in Cuba. Dunnett, Adjiman, and Shah (2008) developed a combined production and logistic model to find the optimal configuration of a lignocellulosic bioethanol SC. Mathematical programming methods associated with plantation planning and scheduling can be found in the works by Grunow, Guenther, and Westinner (2007), Paiva and Morabito (2009); Colin (2009) and Higgins and Laredo (2006).

As observed, most of the aforementioned approaches have focused on the tactical level of the SCM problem covering short/medium-term decisions associated with the SC operation. These methods consider a given SC configuration and attempt to optimize its activities without modifying the existing topology. A general modeling and solution framework for holistically optimizing ethanol infrastructures is currently lacking. Such an approach would enable governments to choose, in advance, the optimum configurations for ethanol production, storage and delivery systems. A systematic tool of this type could play a major role in guiding national and international policy makers towards the best decisions in the transition process from traditional fossil fuels to biofuels. In this article, we fill this research gap by proposing a novel mathematical formulation for the strategic planning of sugar cane SCs along with an efficient solution method that allows to tackle problems of realistic size in moderate CPU times.

2. Problem statement

To formally state the SC design problem, we consider a generic three-echelon SC (production–storage–market) like the

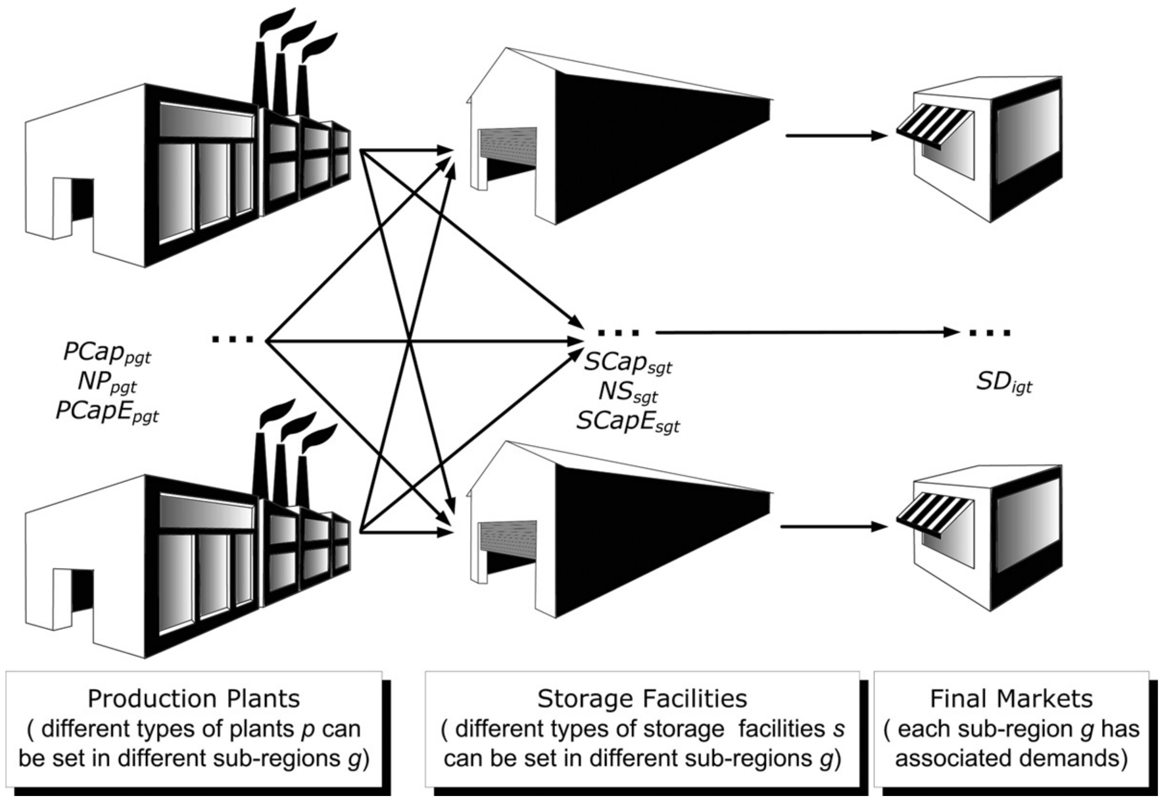

Fig. 1. Structure of the three-echelon ethanol/sugar SC.

one depicted in Fig. 1. This network includes a set of production and storage facilities, and final markets. We assume that we are given a specific region of interest that is divided into a set of sub-regions in which the facilities of the SC can be established in order to cover a given demand. In general, these sub-regions, which are regarded as potential locations for the SC entities, will be defined according to the administrative division of a country. The SC design problem can then be formally stated as follows.

Given are a fixed time horizon, product prices, cost parameters for production, storage and transportation of materials, demand forecast, tax rate, capacity data for plants, storages and transportation links, fixed capital investment data, interest rate, storage holding period and landfill tax. The goal is to determine the configuration of a three-echelon bioethanol network and associated planning decisions with the goal of maximizing the economic performance for a given time horizon. Decisions to be made include the number, location and capacity of production plants and warehouses to be set up in each sub-region, their capacity expansion policy for a given forecast of prices and demand over the planning horizon, the transportation links and transportation modes of the network, and the production rates and flows of feed stocks, wastes and final products.

3. Mathematical model

In this section, we present a mathematical model that considers the specific features of the sugar cane industry, while still being general enough to be easily adapted to any other industrial SC. Particularly, our model is based on the MILP formulation introduced by Almansoori and Shah (2006), and Guillén-Gosálbez et al. (2010), which addresses the design of hydrogen SCs. Furthermore, the model follows the SC formulation developed by Guillén-Gosálbez and Grossmann for the case of petrochemical SCs (Guillén-Gosálbez & Grossmann, 2009b; Guillén-Gosálbez & Grossmann, 2010a), in the way in which the mass balances are handled.

Compared to standard SC formulations that focus on the private sector, the model exhibits two main differentiating features. The first one is that plants, warehouses and final markets share the same potential locations. These locations correspond to the sub-regions in which the overall region of interest is divided. The second one is that the model accounts for the option of opening more than one facility in a given region and time period. This consideration requires the introduction of integer variables that increase the combinatorial complexity of the model. This structure is exploited by our solution algorithm.

As sugar and ethanol share the same feedstock, the proposed model includes integrated infrastructures for ethanol/sugar production. The mathematical formulation considers all possible configurations of the future ethanol/sugar SC as well as all technological aspects associated with the SC performance such as production and storage technologies, waste disposal, modes for transportation of raw materials, products and wastes. We describe next some general features of the model before immersion into a detailed description of its equations.

Production plants

Sugar cane is the leading feedstock for bioethanol production in Argentina as well as in most of the tropical regions all over the world (e.g., Brazil, India, China, etc.). The juice is extracted from sugar cane mainly by milling. From this step sugar cane juice can be treated in different ways. Sugar factories can use this juice to produce white sugar and raw sugar. There are two technologies realizing the "sugar cane-to-sugar" pathway: one of them generates molasses (T1) as a byproduct, whereas the other one provides a secondary honey (T2) in addition to sugars. These two kinds of byproducts are

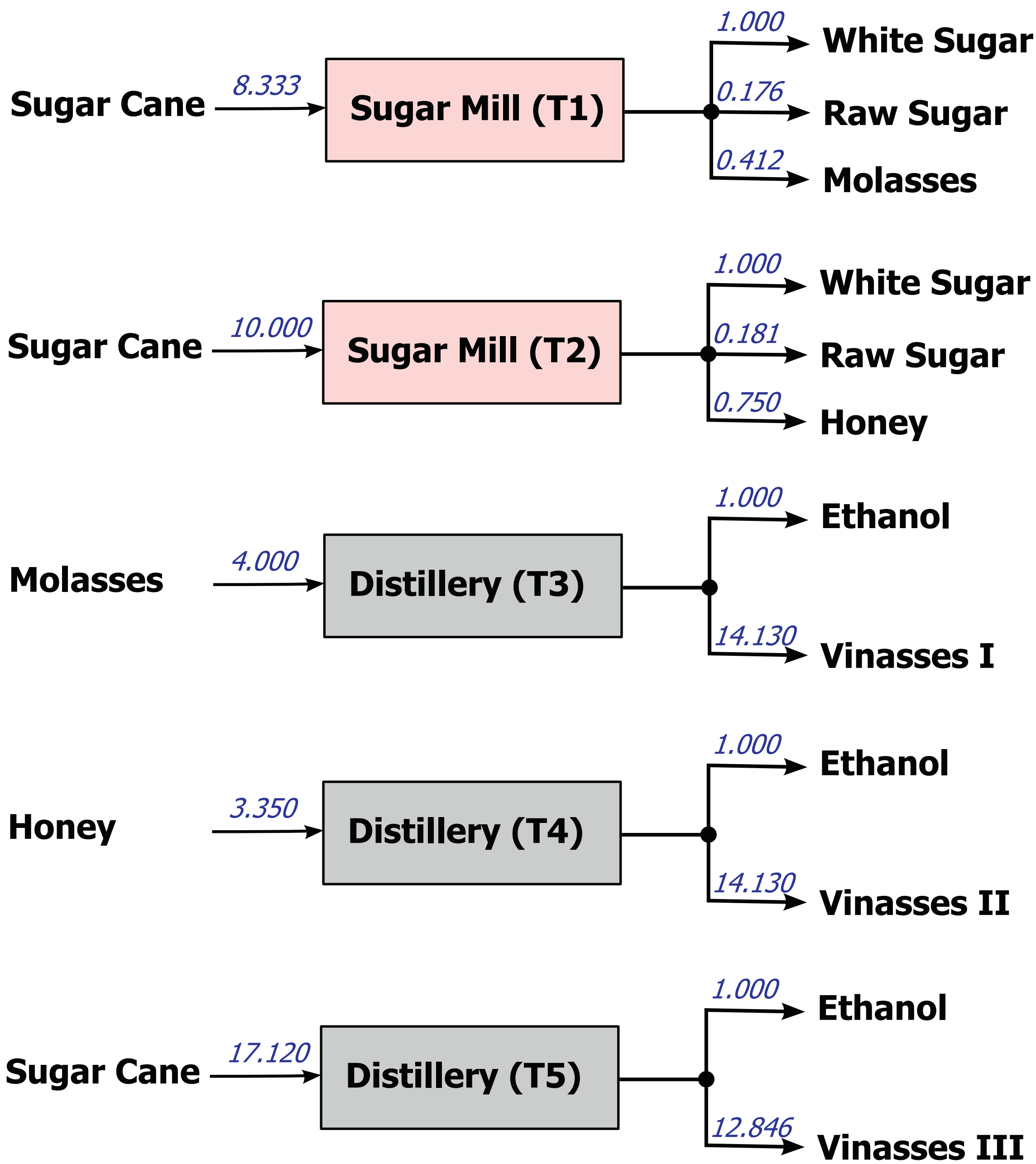

Fig. 2. Set of technologies. The labels T1, T2, . . ., T5 indicate the technology used; the numbers above the arrows correspond to the mass balance coefficients.

distinguished by their sucrose content. Molasses is a viscous dark honey whose low sucrose content cannot be separated by crystallization, while 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 following dehydration of different process streams: molasses (T3), honey (T4) and sugar cane juice (T5). According to this, the model considers 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. We assume that bagasse is completely utilized for internal purposes, so the model includes a set of nine materials: sugar cane, ethanol, molasses, honey, white sugar, raw sugar, vinasse type 1, vinasse type 2 and vinasse type 3.

All the considered technologies require a water feed. For example, sugar mills T1 and T2 use water for the imbibition of the chopped sugar cane. In the technologies T3 and T4, molasses or honey must be diluted before the fermentation step. Distillery T5 utilizes water for two purposes: extraction and dilution of sugar cane juice. We do not consider a water supply, but the cost of water is included in the parameter UPC_{ipgt} (unit production cost).

Each plant type incurs fixed capital and operating costs and may be expanded in capacity over time in order to follow a specific demand pattern. The establishment of a plant type is determined from the demand of the sub-region, the capacity that the sub-region has to fulfill its internal needs and the cost data.

Storage facilities

The model includes two different types of storage facilities: warehouses for liquid products and warehouses for solid materials. Each storage facility type has fixed capital and unit storage costs, and lower and upper limits for capacity expansions. The storage capacity might be expanded in order to follow changes in the demand as well as in the supply.

We do not consider feed storage facilities in the supply chain. The reason for this is that the freshly cut sugar cane must be transported to the factory without any delay, because it loses its sugar content very rapidly. Moreover, damage to the cane during mechanical harvesting accelerates this decline. Hence, the sugar cane must be transported to a sugar mill within 24 hours after harvest at the latest (Shreve & Austin, 1984).

Transportation modes

Transportation links allow to deliver final products to customers, supply the plants with raw materials and dispose the process wastes. The model assumes that the transportation tasks can be performed by three types of trucks: heavy trucks with open-box bed for sugar cane, lorries for sugar and tank trucks for liquid products. Each type of transportation mode has fixed capital and unit transportation costs and lower and upper limits for its capacity. The number and capacity of the transportation links can also vary over time in order to follow a given demand pattern.

3.1. General constraints

We next describe the main mathematical constraints of the model, which have been derived bearing in mind the particular features of the sugar cane industry in Argentina.

Materials balance

The starting point for all design is the material balance. Particularly, the law of conservation of mass must be satisfied in every sub-region. The overall mass balance for each sub-region is represented by Eq. (1). In accordance with it, for every material form i, the initial inventory kept in sub-region g from previous period (ST_{isgt-1}) plus the amount produced (PT_{igt}), the amount of raw materials purchased (PU_{igt}) and the input flow rate from other facilities in the SC ($Q_{ilg'gt}$) must equal the final inventory (ST_{isgt}) plus the amount delivered to customers (DTS_{igt}) plus the output flow to other sub-regions ($Q_{ilgg't}$) and the amount of waste (W_{igt}).

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

In this equation, $SI(i)$ represents the set of technologies that can be used to store product i, whereas $LI(i)$ are the set of transportation modes that can transport product i. Furthermore, the amount of products delivered to the final markets should be less than or equal to the actual demand (SD_{igt}):

$$DTS_{igt} \le SD_{igt} \quad \forall i, g, t \tag{2}$$

Production

The total production rate of material i in sub-region g is determined from the particular production rates (PE_{ipgt}) of each technology p installed in the sub-region:

$$PT_{igt} = \sum_{p} PE_{ipgt} \quad \forall i, g, t \tag{3}$$

The details of each technology, including the mass balance coefficients, are shown in Fig. 2, where residuals, water feed, loses and discards are omitted. As observed, the material balance coefficients of the main products (white sugar and ethanol) have been normalized to 1. The production rates of byproducts and raw materials for each technology are calculated from the material balance coefficients, ρ_{pi}, and the production rates of the main products:

$$PE_{ipgt} = \rho_{pi} PE_{i'pgt} \quad \forall i, p, g, t, \quad \forall i' \in IM(p) \tag{4}$$

In this equation, $IM(p)$ represents the set of main products associated with each technology. The values of the material balance coefficients are negative for feedstocks and positive for products/by-products. The production rate of each technology p in sub-region g is limited by the minimum desired percentage of the available technology that must be utilized, τ, multiplied by the existing capacity (represented by the continuous variable $PCap_{pgt}$) and the maximum capacity:

$$\tau PCap_{pgt} \le PE_{ipgt} \le PCap_{pgt} \quad \forall i, p, g, t \tag{5}$$

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

$$PCap_{pgt} = PCap_{pgt-1} + PCapE_{pgt} \quad \forall p, g, t \tag{6}$$

Eq. (7) bounds the capacity expansion $PCapE_{pgt}$ between upper and lower limits, which are calculated from the number of plants installed in the sub-region (NP_{gpt}) and the minimum and maximum capacities associated with each technology p ($\underline{PCap}_p$ and $\overline{PCap}_p$, respectively).

$$\underline{PCap}_p NP_{pgt} \le PCapE_{pgt} \le \overline{PCap}_p NP_{pgt} \quad \forall p, g, t \tag{7}$$

The purchases of sugar cane are limited by the capacity of the existing sugar cane plantation in sub-region g and time interval t:

$$PU_{igt} \le CapCrop_{gt} \quad \forall i = \text{sugar cane}, g, t \tag{8}$$

Storage

As occurs with plants, the storage capacity is limited by lower and upper bounds, which are given by the number of storage facilities installed in sub-region g (NS_{sgt}) and the minimum and maximum storage capacities ($\underline{SCap}_s$ and $\overline{SCap}_s$, respectively) associated with each storage technology:

$$\underline{SCap}_s NS_{sgt} \le SCapE_{sgt} \le \overline{SCap}_s NS_{sgt} \quad \forall s, g, t \tag{9}$$

The capacity of a storage technology s in any 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 ($SCapE_{sgt}$):

$$SCap_{sgt} = SCap_{sgt-1} + SCapE_{sgt} \quad \forall s, g, t \tag{10}$$

The storage capacity should be enough to store the total inventory (ST_{isgt}) of product i during time interval t:

$$\sum_{i\in IS(s)} ST_{isgt} \le SCap_{sgt} \quad \forall s, g, t \tag{11}$$

In this equation, $IS(s)$ denotes the set of products that can be stored by technology s. During steady-state operation, the average inventory (AIL_{igt}) is a function of the amount delivered to customers and the storage period β:

$$AIL_{igt} = \beta DTS_{igt} \quad \forall i, g, t \tag{12}$$

The storage capacity ($SCap_{sgt}$) that should be established in a sub-region in order to cope with fluctuations in both supply and demand, is twice the average inventory levels of products i (Simchi-Levi, Kamisky, & Simchi-Levi, 2000).

$$2AIL_{igt} \le \sum_{s\in SI(i)} SCap_{sgt} \quad \forall i, g, t \tag{13}$$

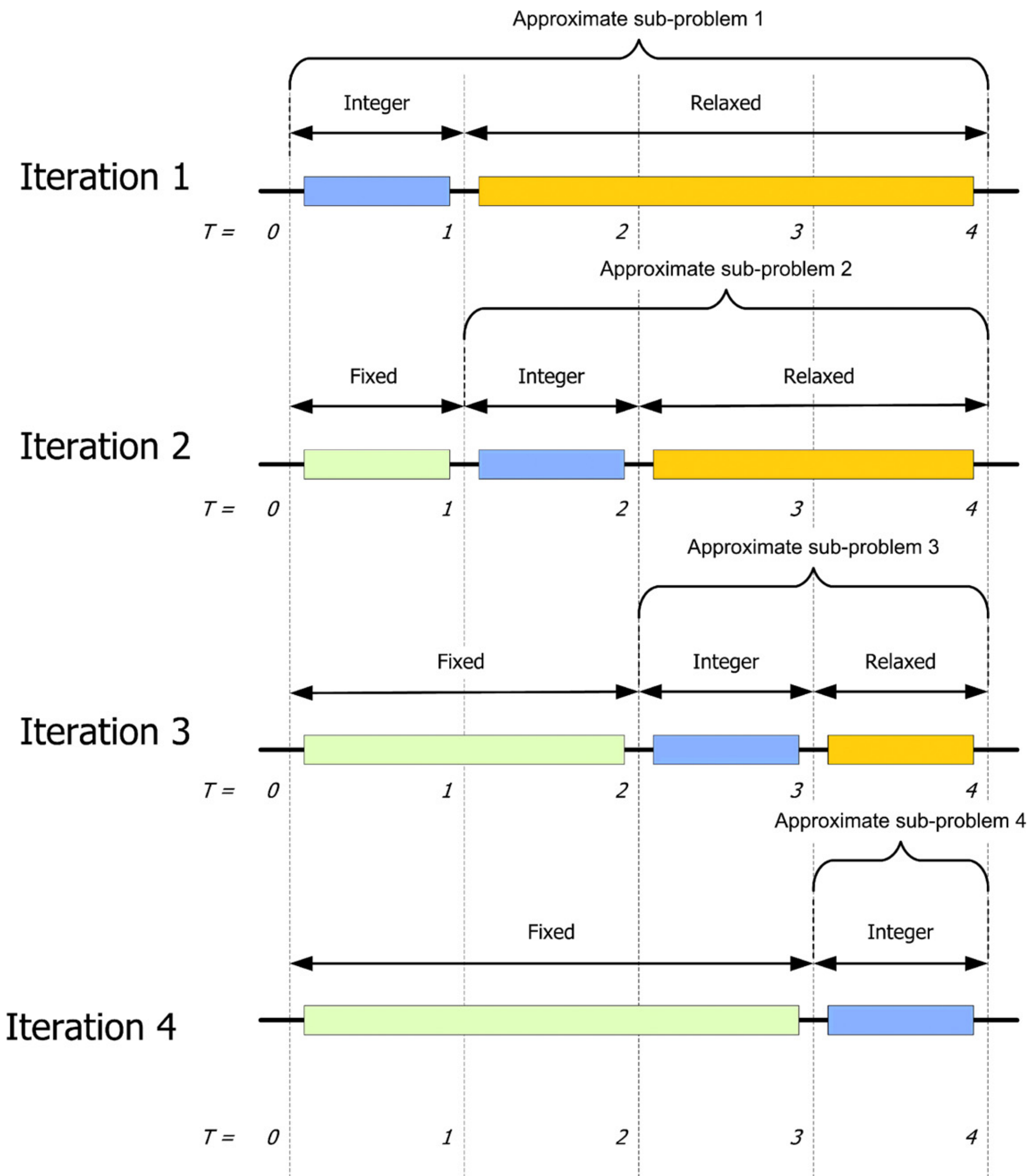

Fig. 3. Application of the "rolling horizon" strategy to a four-time-period problem.

Transportation

The existence of a transportation link between two sub-regions g and g' is represented by a binary variable $X_{lgg't}$ which equals 1 if a transportation link is established between the two sub-regions and 0 otherwise. The definition of this variable is enforced via Eq. (14), which constraints the materials flow between minimum and maximum allowable capacity limits ($\underline{Q_l}$ and $\overline{Q_l}$, respectively):

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

In this equation, $IL(l)$ represents the set of materials that can be transported via transportation mode l. Furthermore, a sub-region can either import or export material i, but not both at the same time:

$$X_{lgg't} + X_{lg'gt} = 1 \quad \forall l, t, g, g'(g' \neq g) \tag{15}$$

3.2. Objective function

The use of *NPV* as an objective function is a widely-spread approach in investment planning. In most cases it results in a linear model, which can be effectively solved by standard branch-and-bound methods. However, the *NVP* measure does not account appropriately for the rate at which the investment is recovered because it tends to add investment that has marginal or meaningless returns. Bagajewicz (2008) pointed out that additional procedures and measures are needed in planning problems. Particularly, the return of investment (*ROI*) is a more appropriate key performance indicator when there are other investment alterna-

Table 1
Mean values for demand, ton/year.

Name of province	Associated sub-region	Product form		
		White sugar	Raw sugar	Ethanol
Buenos Aires	G01	76,614.92	38,307.46	84,276.41
Córdoba	G02	84,126.19	42,063.09	92,538.81
Corrientes	G03	25,438.16	12,719.08	27,981.97
La Plata	G04	379,268.90	189,634.45	417,195.79
La Rioja	G05	9714.57	4857.29	10,686.03
Mendoza	G06	43,565.35	21,782.67	47,921.88
Neuquén	G07	13,720.58	6860.29	15,092.64
Entre Rios	G08	31,547.32	15,773.66	34,702.05
Misiones	G09	27,140.71	13,570.36	29,854.78
Chubut	G10	11,517.28	5758.64	12,669.00
Chaco	G11	26,439.66	13,219.83	29,083.63
Santa Cruz	G12	5708.56	2854.28	6279.42
Salta	G13	30,746.12	15,373.06	33,820.73
San Juan	G14	17,526.29	8763.14	19,278.92
San Luis	G15	11,016.52	5508.26	12,118.18
Tucumán	G16	37,155.73	18,577.87	40,871.31
Jujuy	G17	17,125.69	8562.84	18,838.26
Santa Fe	G18	81,121.68	40,560.84	89,233.85
La Pampa	G19	8412.62	4206.31	9253.88
Santiago del Estero	G20	21,732.60	10,866.30	23,905.86
Catamarca	G21	8612.92	4306.46	9474.21
Río Negro	G22	15,022.53	7511.27	16,524.79
Formosa	G23	13,520.28	6760.14	14,872.31
Tierra del Fuego	G24	3204.81	1602.40	3525.29

tives competing for the same capital. In the context of a SC design problem like the one addressed in this article, one way in which this metric can be evaluated is using the ratio between the average cash flows (CF_t) and the fixed capital investment FCI:

$$ROI = \frac{\left(\sum_t CF_t\right)/T}{FCI} \tag{16}$$

As observed, the introduction of the *ROI* as the economic indicator to be maximized gives rise to a mixed-integer linear fractional programming formulation that can be solved using the Dinkelbach's algorithm. Given that the linear NPV-based approach already has computational issues that this paper attempts to ameliorate, following Bagajewicz (2008) we resort to solving a series of MILPs that maximize the *NPV* for different upper bounds on *FCI*. As discussed in Bagajewicz (2008), from these results one can identify solutions close to the maximum *ROI* one.

The *NPV* can be determined from the discounted cash flows generated in each of the time intervals *t* in which the total time horizon is divided:

$$NPV = \sum_t \frac{CF_t}{(1+ir)^{t-1}} \tag{17}$$

In this equation, *ir* represents the interest rate. The cash flow that appears in Eq. (17) in each time period is computed from the net earnings NE_t (i.e., profit after taxes), and the fraction of the total depreciable capital ($FTDC_t$) that corresponds to that period as follows:

$$CF_t = NE_t - FTDC_t, \quad t = 1, \ldots, T-1 \tag{18}$$

In the calculation of the cash flow of the last time period ($t = T$), we assume that part of the total fixed capital investment may 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.

$$CF_t = NE_t - FTDC_t + svFCI, \quad t = T \tag{19}$$

Table 2
Distances between sub-regions, km.

	G01	G02	G03	G04	G05	G06	G07	G08	G09	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G20	G21	G22	G23	G24
G01	0	711	933	60	1167	1080	1178	511	1008	1379	953	2542	1542	1140	800	1229	1565	484	607	1070	1122	948	1098	3162
G02	711	0	900	768	460	680	1153	360	1118	1524	880	2638	844	600	420	597	867	340	667	439	433	1208	1031	3258
G03	933	900	0	990	1024	1490	1913	573	335	2206	20	3369	830	1460	1190	794	853	540	1388	635	857	1774	186	3989
G04	60	768	990	0	1224	1137	1159	568	1065	1371	1010	2533	1599	1197	857	1286	1622	541	664	1127	1173	924	1236	3153
G05	1167	460	1024	1224	0	612	1427	820	1333	1872	1007	3087	704	355	559	382	727	800	1015	389	171	1565	1139	3707
G06	1080	680	1490	1137	612	0	815	952	1710	1628	1470	2783	1311	166	264	872	1329	930	789	1007	725	1342	1600	3403
G07	1178	1153	1913	1159	1427	815	0	1413	2075	746	1880	1909	1997	981	890	1581	2020	1373	535	1618	1536	557	2020	2529
G08	511	360	573	568	820	952	1413	0	758	1715	590	2887	1107	950	691	794	1130	30	855	635	803	1252	746	3507
G09	1008	1118	335	1065	1333	1710	2075	758	0	2356	332	3511	1142	1708	1449	1086	1165	785	1518	927	1179	1896	508	4131
G10	1379	1524	2206	1371	1872	1628	746	1715	2356	0	2236	1172	2308	1705	1382	2107	2331	1685	857	1986	1900	809	2450	1792
G11	953	880	20	1010	1007	1470	1880	590	332	2236	0	3388	813	1460	1190	774	833	540	1368	618	820	1756	173	4008
G12	2542	2638	3369	2533	3087	2783	1909	2887	3511	1172	3388	0	3482	2868	2545	3192	3505	2850	2020	3070	3167	1952	3593	620
G13	1542	844	830	1599	704	1311	1997	1107	1142	2308	813	3482	0	1150	1264	310	90	1077	1462	472	533	2066	959	4102
G14	1140	600	1460	1197	355	166	981	950	1708	1705	1460	2868	1150	0	320	708	1163	920	848	840	497	1509	1540	3488
G15	800	420	1190	857	559	264	890	691	1449	1382	1190	2545	1264	320	0	838	1287	660	525	859	674	1087	1345	3165
G16	1229	597	794	1286	382	872	1581	794	1086	2107	774	3192	310	708	838	0	328	764	1257	164	221	1803	925	3812
G17	1565	867	853	1622	727	1329	2020	1130	1165	2331	833	3505	90	1163	1287	328	0	1092	1485	490	563	2095	921	4125
G18	484	340	540	541	800	930	1373	30	785	1685	540	2850	1077	920	660	764	1092	0	828	605	777	1218	709	3470
G19	607	667	1388	664	1015	789	535	855	1518	857	1368	2020	1462	848	525	1257	1485	828	0	1129	1065	580	1492	2640
G20	1070	439	635	1127	389	1007	1618	635	927	1986	618	3070	472	840	859	164	490	605	1129	0	234	1669	751	3690
G21	1122	433	857	1173	171	725	1536	803	1179	1900	820	3167	533	497	674	221	563	777	1065	234	0	1645	985	3787
G22	948	1208	1774	924	1565	1342	557	1252	1896	809	1756	1952	2066	1509	1087	1803	2095	1218	580	1669	1645	0	1922	2572
G23	1098	1031	186	1236	1139	1600	2020	746	508	2450	173	3593	959	1540	1345	925	921	709	1492	751	985	1922	0	4213
G24	3162	3258	3989	3153	3707	3403	2529	3507	4131	1792	4008	620	4102	3488	3165	3812	4125	3470	2640	3690	3787	2572	4213	0

Table 3
Sugar cane capacity, ton/year.

Province	Capacity
Tucumán	12,220,000
Jujuy	4,324,000
Salta	2,068,000
Santa Fe	125,960
Misiones	62,040

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

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

	α^{PL}_{pgt}, \$	β^{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.

	α^{S}_{sgt}, \$	β^{S}_{sgt}, \$ year/ton
S1	1,220,000	122
S2	18,940,000	1894

The net earnings are given by the difference between the incomes (Rev_t) and the facility operating (FOC_t), and transportation cost (TOC_t), as it is stated in Eq. (20):

$$NE_t = (1-\varphi)(Rev_t - FOC_t - TOC_t) + \varphi DEP_t \quad \forall t \tag{20}$$

In this equation, φ denotes the tax rate. The revenues are determined from the sales of final products and the corresponding prices

Table 7
Prices of final products.

	Price, \$/ton
White sugar [a]	734
Raw sugar [b]	615
Ethanol [c]	598

[a] No. 407 LIFFE white sugar futures contract
[b] No. 11 ICE raw sugar futures contract
[c] QE NYMEX ethanol futures contract

Table 8
Parameters used to calculate the capital and operating cost for different transportation modes.

	Heavy truck	Lorry	Tanker truck
Average speed (km/h)	55	60	60
Capacity (ton/trip)	30	25	20
Availability of transportation mode (h/day)	18	18	18
Cost of establishing transportation mode (\$)	90,000	65,000	100,000
Driver wage (\$/h)	10	10	10
Fuel economy (km/L)	5	5	5
Fuel price (\$/L)	0.85	0.85	0.85
General expenses (\$/day)	8.22	8.22	8.22
Load/unload time of product (h/trip)	6	6	6
Maintenance expenses (\$/km)	0.0976	0.0976	0.0976

(PR_{igt}):

$$Rev_t = \sum_{i \in SEP} \sum_{g} DTS_{igt} PR_{igt} \quad \forall t \tag{21}$$

In this equation SEP 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_{ipgt} and USC_{isgt}, respectively) by the corresponding production rates and average inventory levels, respectively. This term includes also the disposal cost (DC_t):

$$FOC_t = \sum_{i} \sum_{g} \sum_{i \in IM(p)} UPC_{ipgt} PE_{ipgt} + \sum_{i} \sum_{g} \sum_{i \in IS(s)} USC_{isgt} AIL_{igt} + DC_t \quad \forall t \tag{22}$$

Table 9
Comparison of "full space" method and "rolling horizon" approach.

Case	"Full space" solution	CPU [a]	"Rolling horizon" approach								
			0% [b]	CPU	Error	0.5% [c]	CPU	Error	1% [d]	CPU	Error
2	364,855,004	249	355,681,928	165	2.514%	355,681,928	159	2.514%	355,681,928	133	2.514%
3	748,077,521	190	737,299,005	137	1.441%	747,059,134	110	0.136%	747,059,134	71	0.136%
4	1,103,078,130	387	1,102,408,378	420	0.061%	1,100,709,014	254	0.215%	1,072,612,733	122	2.762%
5	1,488,103,667	975	1,481,385,696	428	0.451%	1,473,161,834	285	1.004%	1,481,093,288	56	0.471%
6	1,800,100,718	4,915	1,793,499,301	880	0.367%	1,794,272,262	378	0.324%	1,792,417,632	110	0.427%
7	2,073,908,387	14,468	2,065,178,757	1996	0.421%	2,066,786,891	687	0.343%	2,071,299,494	128	0.126%
8	2,382,730,430	27,608	2,372,869,869	2548	0.414%	2,373,873,363	702	0.372%	2,370,793,357	345	0.501%
9	2,599,013,033 [e]	43,200	2,591,023,707	7,140	0.487%	2,574,336,476	1,928	1.128%	2,592,387,982	455	0.435%
10	2,790,699,079 [e]	43,200	2,791,675,712	3,637	0.356%	2,785,727,849	2,415	0.569%	2,756,152,808	308	1.624%

[a] CPU time in seconds.
[b] Solution calculated by the "rolling-horizon" method solving the sub-problems with 0% of optimality gap.
[c] Solution calculated by the "rolling-horizon" method solving the sub-problems with 0.5% of optimality gap.
[d] Solution calculated by the "rolling-horizon" method solving the sub-problems with 1% of optimality gap.
[e] Best integer solution after 12 h.

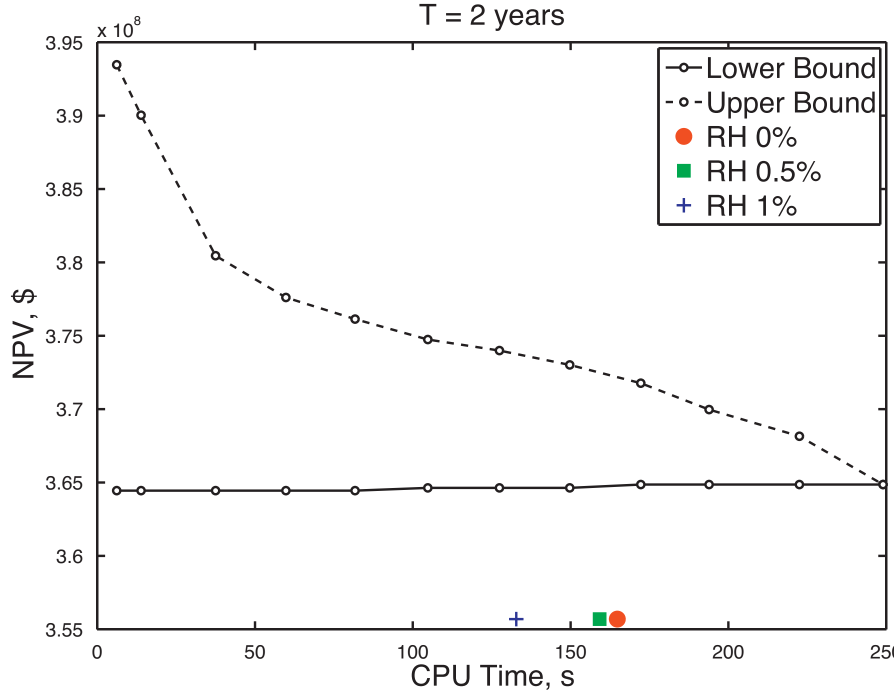

Fig. 4. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a two-time-period problem.

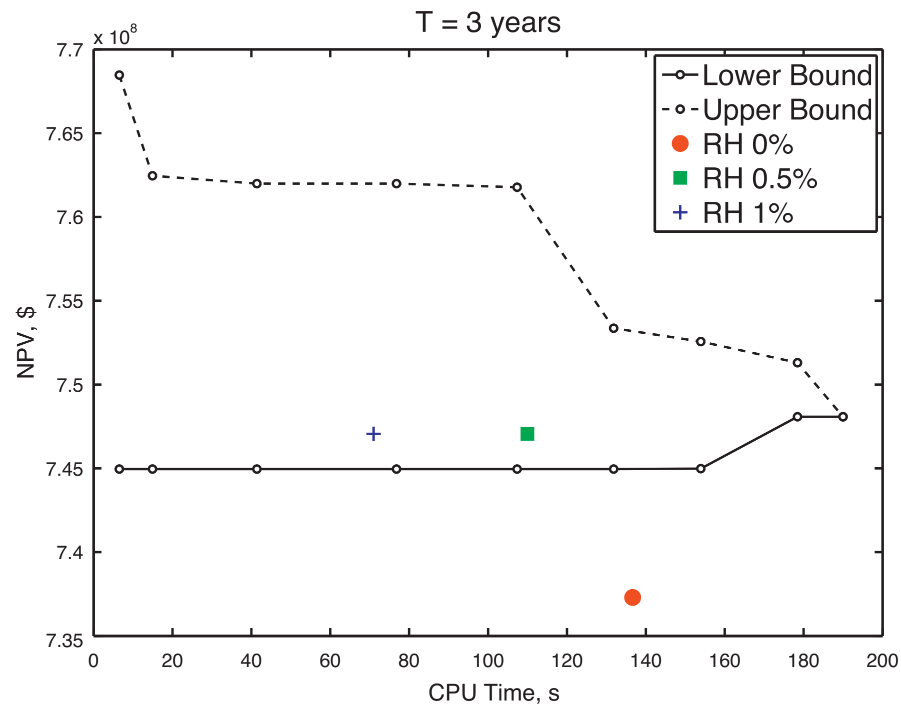

Fig. 5. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a three-time-period problem.

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

$$DC_t = \sum_i \sum_g W_{igt} LT_{ig} \quad \forall t \tag{23}$$

The transportation cost includes the fuel (FC_t), labour (LC_t), maintenance (MC_t) and general (GC_t) costs:

$$TOC_t = FC_t + LC_t + MC_t + GC_t \quad \forall t \tag{24}$$

The fuel cost is a function of the fuel price (FP_{lt}) and fuel usage:

$$FC_t = \sum_g \sum_{g' \neq g} \sum_l \sum_{i \in IL(l)} \left[\frac{2EL_{gg'} Q_{ilgg't}}{FE_l TCap_l} \right] FP_{lt} \quad \forall t \tag{25}$$

In Eq. (25), the fractional term represents the fuel usage, and is determined from the total distance traveled in a trip ($2EL_{gg'}$), the fuel consumption of transport mode l (FE_l) and the number of trips made per period of time ($Q_{ilgg't}/TCap_l$). Note that this equation

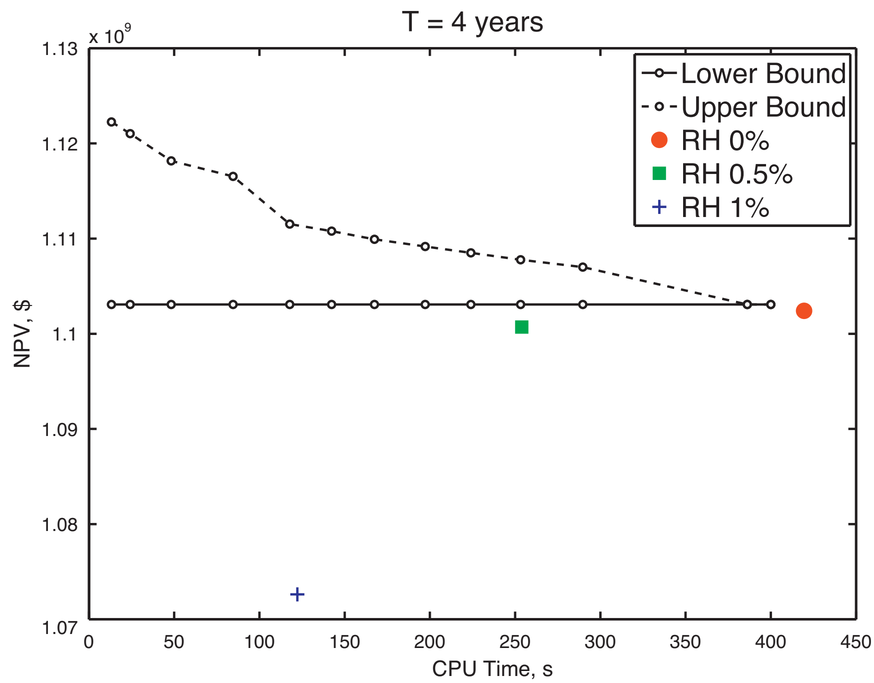

Fig. 6. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a four-time-period problem.

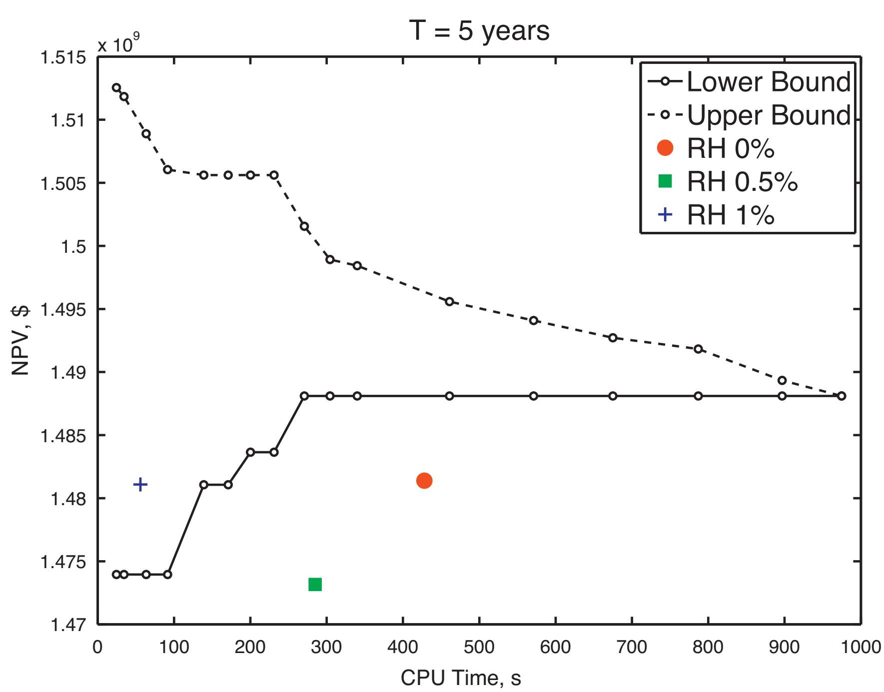

Fig. 7. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a five-time-period problem.

assumes that the transportation units operate only between two predefined sub-regions. Furthermore, as shown in Eq. (26), the labor transportation cost is a function of the driver wage (DW_{lt}) and total delivery time (term inside the brackets):

$$LC_t = \sum_g \sum_{g' \neq g} \sum_l DW_{lt} \sum_{i \in IL(l)} \left[\frac{Q_{ilgg't}}{TCap_l} \left(\frac{2EL_{gg'}}{SP_l} + LUT_l \right) \right] \quad \forall t \qquad (26)$$

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

$$MC_t = \sum_g \sum_{g' \neq g} \sum_l \sum_{i \in IL(l)} ME_l \frac{2EL_{gg'} Q_{ilgg't}}{TCap_l} \quad \forall t \qquad (27)$$

Finally, the general cost includes the transportation insurance, license and registration, and outstanding finances. It can be deter-

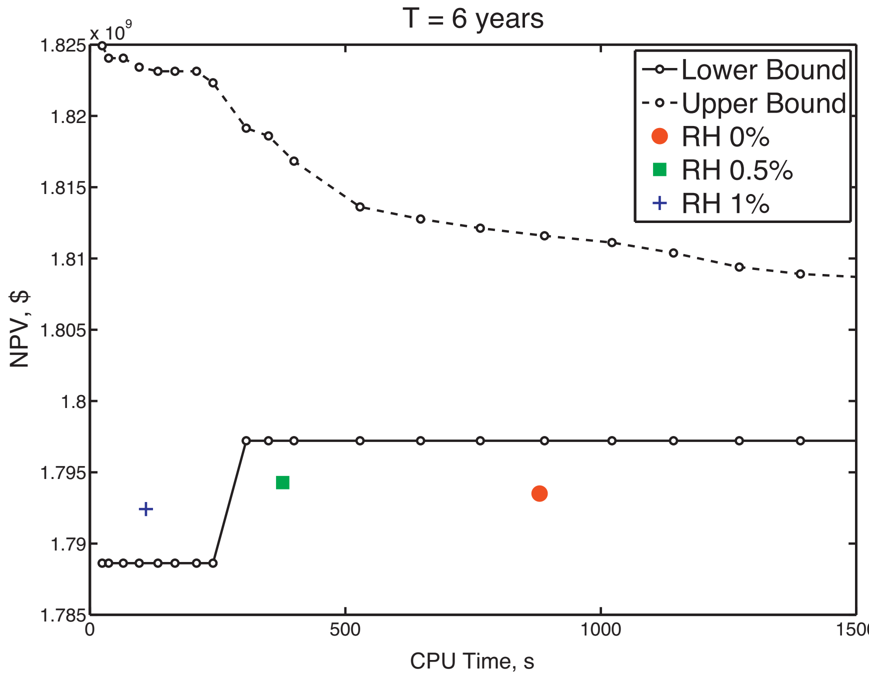

Fig. 8. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a six-time-period problem.

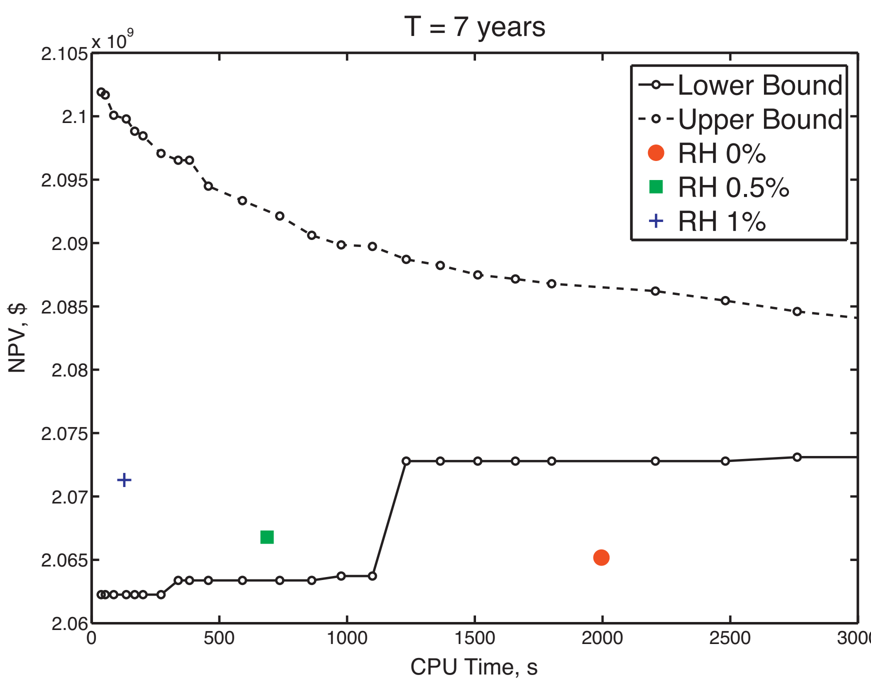

Fig. 9. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a seven-time-period problem.

mined from the unit general expenses (GE_{lt}) and number of transportation units (NT_{lt}), as follows:

$$GC_t = \sum_{l} \sum_{t' \le t} GE_{lt} NT_{lt'} \quad \forall t \tag{28}$$

The depreciation term is calculated with the straight-line method:

$$DEP_t = \frac{(1 - sv)FCI}{T} \quad \forall t \tag{29}$$

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

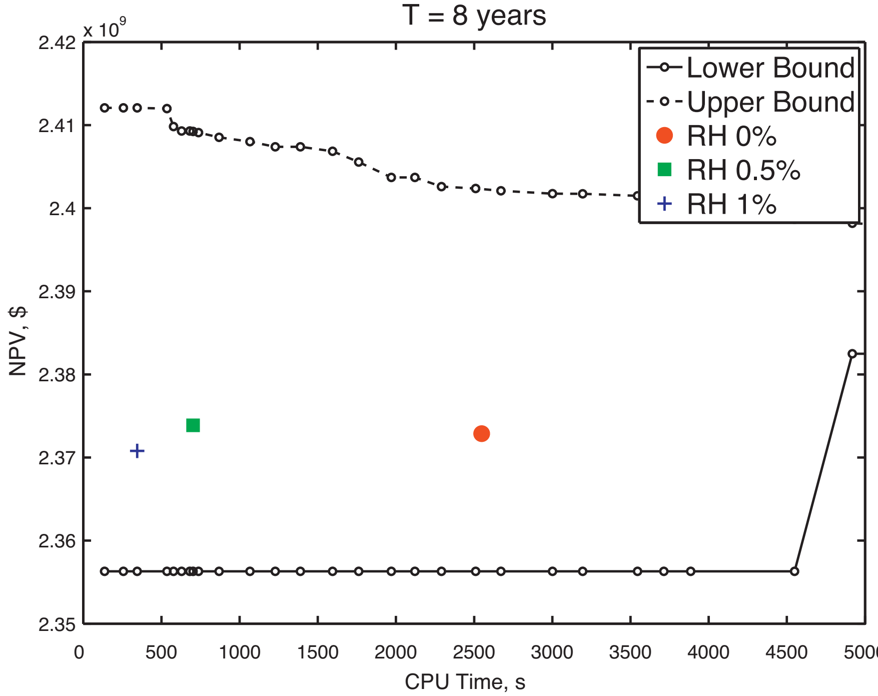

Fig. 10. Comparison of “full space” method vs. “rolling horizon” algorithm (for different optimality gaps imposed on the sub-problems) applied to an eight-time-period problem.

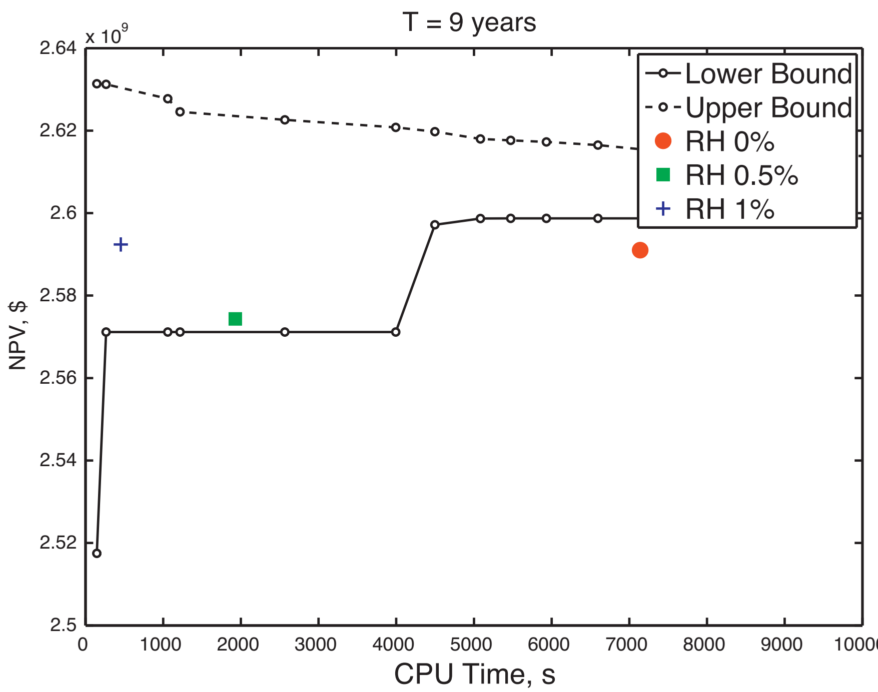

Fig. 11. Comparison of “full space” method vs. “rolling horizon” algorithm (for different optimality gaps imposed on the sub-problems) applied to a nine-time-period problem.

entire time horizon as follows:

$$FCI = \sum_p \sum_g \sum_t (\alpha^{PL}_{pgt} NP_{pgt} + \beta^{PL}_{pgt} PCapE_{pgt}) + \sum_s \sum_g \sum_t (\alpha^{S}_{sgt} NS_{sgt} + \beta^{S}_{sgt} SCapE_{sgt}) + \sum_l \sum_t (NT_{lt} TMC_{lt}) \quad (30)$$

Here, the parameters α^{PL}_{pgt}, β^{PL}_{pgt} and α^{S}_{sgt}, β^{S}_{sgt} are the fixed and variable investment terms corresponding to plants and warehouses, respectively. On the other hand, TMC_{lt} is the investment cost associated with transportation mode l. The average number of trucks required to satisfy a certain flow between different sub-regions is computed 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

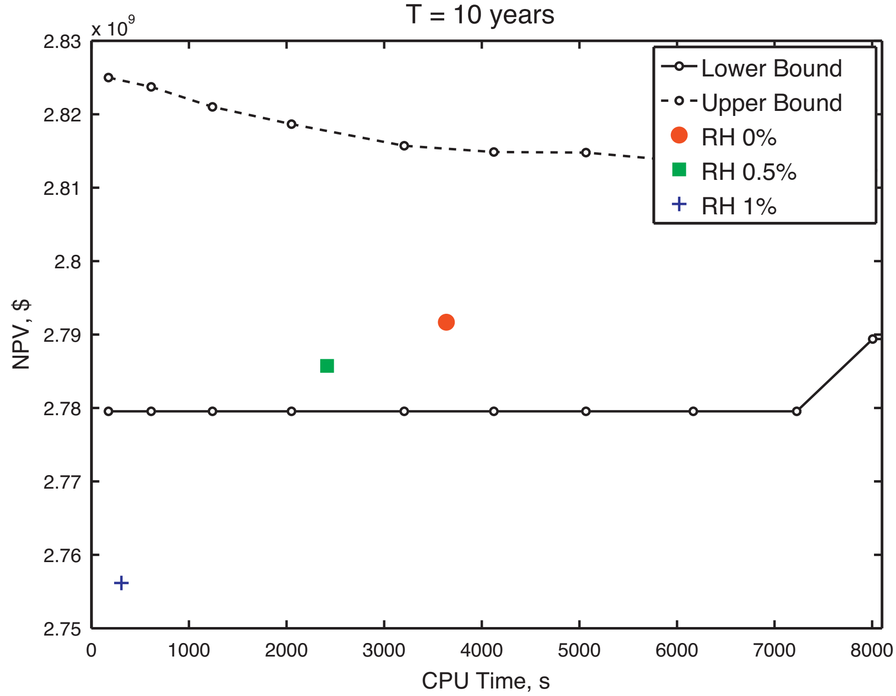

Fig. 12. Comparison of "full space" method vs. "rolling horizon" algorithm (for different optimality gaps imposed on the sub-problems) applied to a ten-time-period problem.

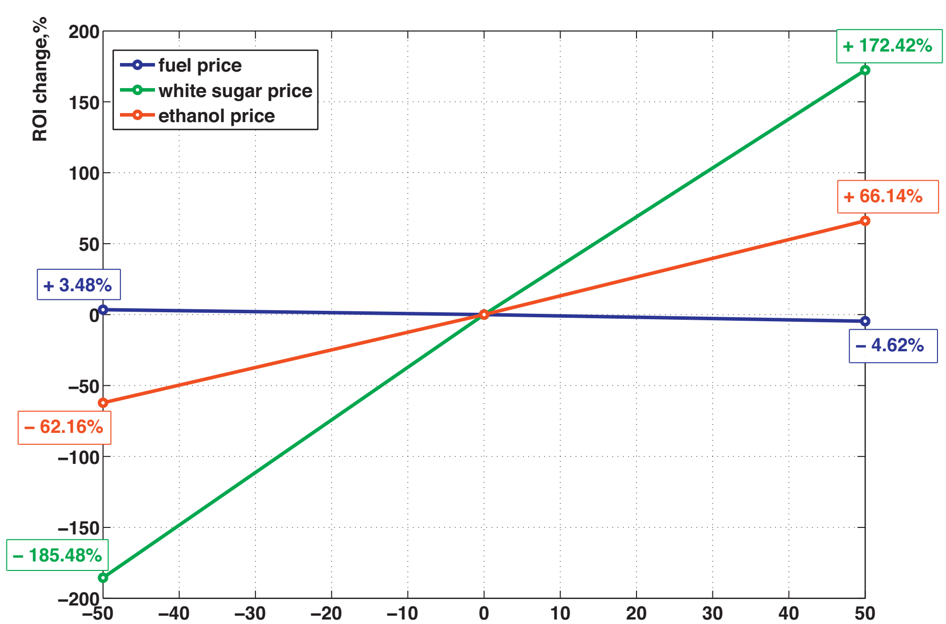

Fig. 13. Influence of fuel, sugar and ethanol prices on ROI.

stated in Eq. (31):

$$\sum_{t \le T} NT_{lt} \ge \sum_{i \in IL(l)} \sum_{g} \sum_{g' \ne g} \sum_{t} \frac{Q_{ilgg't}}{avl_l TCap_l} \left(\frac{2EL_{gg'}}{SP_l} + LUT_l \right) \quad \forall l \tag{31}$$

The total amount of capital investment can be constrained to be lower than an upper limit, as stated in Eq. (32):

$$FCI \le \overline{FCI} \tag{32}$$

Finally, the model assumes that the depreciation is linear over the time horizon. Thus, the depreciation term ($FTDC_t$) is calculated as follows:

$$FTDC_t = \frac{FCI}{T} \quad \forall t \tag{33}$$

Finally, the overall MILP formulation is stated in compact form as follows:

$$\max_{x,X,N} NPV(x, X, N) \qquad (P)$$

$$\text{s.t. constraints } 1\text{–}33$$

$$x \subset \mathbb{R}, \quad X \subset \{0, 1\}, \quad N \subset \mathbb{Z}^+$$

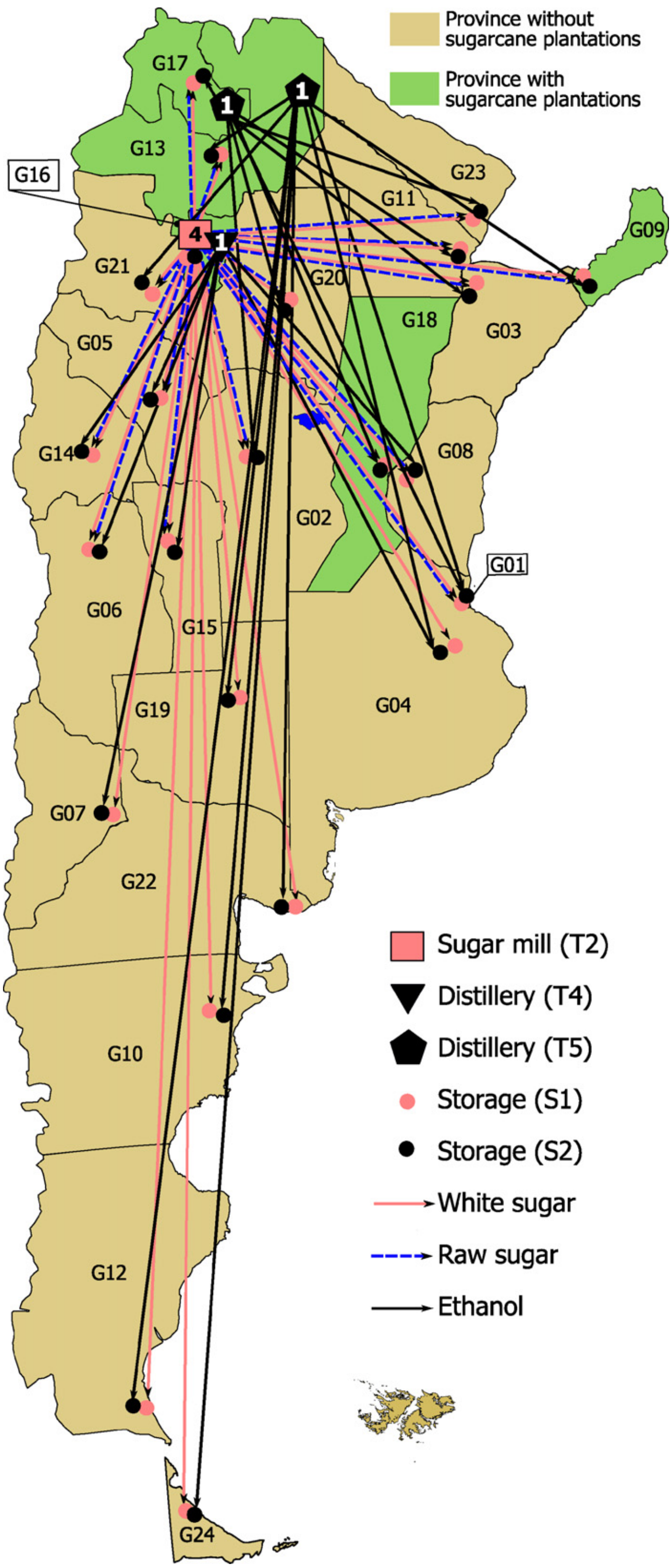

Fig. 14. Configuration of SC under base level of prices, high level of sugar price, low level of ethanol price, and all levels of fuel price.

Here, x denotes the continuous variables of the problem (capacity expansions, production rates, inventory levels and materials flows), X represents the binary variables (i.e., establishment of transportation links), and N is the set of integer variables denoting the number of plants, storage facilities and transportation units of each type selected.

The section that follows describes how the MILP problem described above can be efficiently solved via a customized rolling horizon algorithm, thus expediting the overall search for SC configurations that yield large *ROI* values.

4. Solution approach

As shown in the previous section, the MILP model includes decision variables of different nature. The variables which represent the number of production and storage facilities to be installed (NP_{gpt} and NS_{sgt}, respectively) and number of transport modes purchased (NT_{lt}) are integer. Variables $X_{lgg't}$ denoting the existence of transportation links between sub-regions are binary, whereas the remaining variables are continuous. The overall MILP formulation can be solved via branch-and-bound techniques. The complexity of this MILP is mainly given by the number of integer and binary variables, which in our case increases with the number of time periods and sub-regions. Large-scale problems can therefore lead to branch-and-bound trees with a prohibitive number of nodes thus making the MILP computationally intractable. A decomposition method is presented next to reduce the computation burden of the model and facilitate the solution of problems of large size that might be found in practice.

The approach presented is based on a “rolling horizon” scheme (Balasubramanian & Grossmann, 2004; Dimitriadis et al., 1997; Elkamel & Mohindra, 1999), and consists of decomposing the original problem (P) into a number of smaller sub-problems that are solved in a sequential way. A typical “rolling horizon” algorithm relies on an approximate model (i.e., simplification of the original problem) that is formulated for the entire horizon of T time periods. In the first iteration, this model is solved providing decisions for the entire horizon, but only those belonging to the first time period are implemented. In the next iteration, the state of the system is updated, and another approximate model is solved for the remaining $T-1$ time periods, freezing the decisions of the first time period already solved. The algorithm proceeds in this manner until all the decisions of the entire time horizon are calculated.

The traditional “rolling horizon” approach relies on solving a sequence of sub-problems of fixed length. This method is not directly applicable to our problem, mainly because there are constraints in our model that impose conditions that must be satisfied over the entire time horizon. Furthermore, the *NPV* calculation requires information from different time periods, which makes it difficult to implement the traditional “rolling horizon approach.

Particularly, to derive the approximate models used by our “rolling horizon” strategy, we exploit the fact that the relaxation of the integer variables of the full space formulation (P) is very tight. In other words, the solution that is obtained when (P) is solved defining *NP*, *NS*, and *NT* as continuous variables rather than as integers, is very close to the optimal solution of the original problem. The reason for this is that in practice these integer variables take large values, since they represent the number of facilities to be established in big regions that cover high demands.

Hence, the approximate models of our algorithm are constructed by relaxing the integer variables denoting the number of transportation units and production and storage facilities established in periods beyond the first one. The motivation behind this

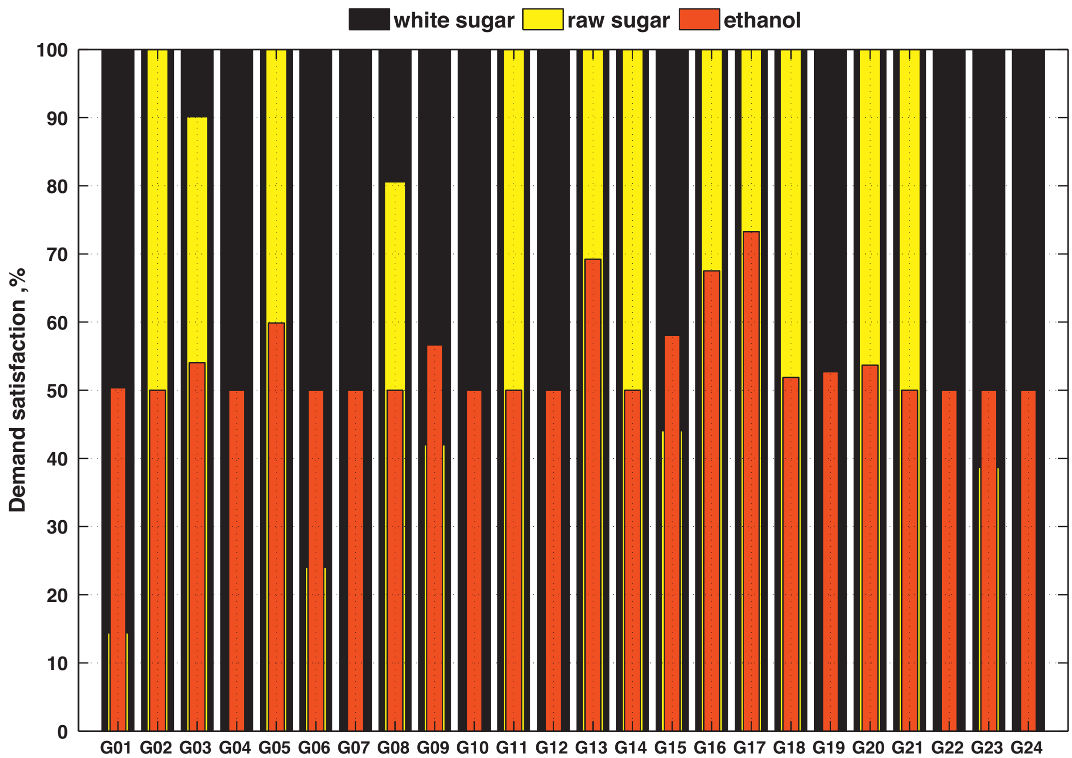

Fig. 15. Demand satisfaction level under base level of prices and high level of sugar prices.

procedure is that the computational complexity is greatly reduced by dropping the integrality requirement on these variables without sacrificing too much the quality of the solution. Therefore, in each iteration the method concentrates on determining the values of the integer variables of one single period, whereas the relaxed part of the problem allows to assess in an approximate manner the effect that these decisions have on later periods. The solutions of these sub-problems, all of which are relaxations of the original full space model (P), are then used to approximate the optimal solution of (P). Each sub-problem (AP) can therefore be expressed as follows:

$$\max_{x,X,N} NPV(x, X, N) \qquad \text{(AP)}$$
$$\text{s.t. constraints } 1\text{–}33$$
$$N = (N' \cup RN)$$
$$x \subset \mathbb{R}, \quad RN \subset \mathbb{R}, \quad X \subset \{0, 1\}, \quad N' \subset \mathbb{Z}^+$$

where $N' = (NP_{pgt'}, NS_{sgt'}, NT_{lt'})$ denotes the vector of integer variables corresponding to time period t' and $RN = (RNP_{pgt}, RNS_{sgt}, RNT_{lt})$ is the vector of continuous variables representing the strategic decisions associated with those time intervals beyond t' (i.e. $t > t'$). The “rolling horizon” algorithm proposed in this work is as follows:

1. **Initialization**.
   Set iteration counter (ctr) equal to 1.
   Go to step 2.
2. **Solution**.
   Solve the subproblem (AP) with the branch-and-bound method relaxing the variables corresponding to those periods beyond ctr.
   Fix the variables for time interval $t = ctr$.
3. **Termination check**.
   If $ctr < T$, then set $ctr = ctr + 1$ and go to step 2.
   Otherwise, there are no more sub-problems to be solved (termination).

Fig. 3 illustrates the way in which the algorithm would proceed for a problem with 4 time periods. Note that the time horizon of each approximate sub-problem is divided into two time blocks:

1. The “integer block”, which covers the first period of the sub-problem and in which all the integer decision variables NP_{pgt}, NS_{sgt} and NT_{lt} remain unchanged. Note that this first interval moves forward as iterations proceed.
2. The “relaxed block”, which comprises all the periods beyond the current one, in which the integer variables denoting the number of production plants, storage facilities and transportation units are relaxed into continuous variables RNP_{pgt}, RNS_{sgt} and RNT_{lt}, respectively.

Remarks

- Before implementing the decomposition strategy, it is convenient to check the tightness of the integer relaxation of the model for small instances of the problem. If the relaxation is not tight enough, the method is not likely to work properly. In this case, alternative methods can be used (see Guillén-Gosálbez et al., 2010).
- The sub-problems can be constructed by relaxing only some of the integer variables instead of all of them. To choose the variables to be relaxed, one can perform a preliminary analysis in order to assess the impact of relaxing the variable on the CPU time and quality of the relaxation.

- The complexity of the model grows with the number of time periods, sub-regions and technologies. By merging neighboring sub-regions with low and high demands one can reduce the overall complexity of the model.
- It is not necessary to solve the sub-problems of the rolling-horizon method to global optimality. In fact, the overall method can be expedited by solving the sub-problems (AP) for low optimality gaps (i.e., less than 5%). This reduction in CPU time might be achieved at the expense of compromising the quality of the final solution.

5. Case study

In order to illustrate the capabilities and advantages of the proposed approach, a case study based on the sugar cane industry of Argentina was solved, comparing the results obtained by the full space branch-and-bound method with those reported by the approximate algorithm.

The problem consists of 24 sub-regions representing original Argentinean provinces with corresponding demand of sugar and ethanol. The sub-regions and demand values corresponding to the first time period are shown in Table 1, whereas the demand for the remaining periods is provided as supplementary material. Distances between sub-regions were determined considering the capitals of the corresponding provinces and the main roads connecting these capitals. These data are listed in Table 2.

We assume that each sub-region has an associated sugar cane capacity. Particularly, sugar cane plantations are situated in five Argentinean provinces, whose production capacities are given in Table 3. The remaining regions have the option of importing sugar cane from these provinces, which may eventually lead to an increase in the transport operating cost. 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 200 and 2 billion tons, respectively. The unit storage cost is assumed to be \$0.365/(ton year) for all types of materials. Fixed and variable investment coefficients for different production and storage modes are listed in Tables 5 and 6, respectively. The prices for final products obtained from actual trading data are presented in Table 7. Unit production cost for sugar and ethanol are equal to \$265/ton and \$317/ton, respectively. The parameters used to calculate the capital and operating cost for different transportation modes can be found in Table 8. 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.

5.1. Computational performance of the "rolling horizon" approach as compared to the NPV-based MILP

To highlight the computational performance of the proposed "rolling horizon" algorithm as compared to a "full space" branch-and-bound method, nine example problems were solved maximizing *NVP* as single objective. Because the issue is to highlight the computational advantages, there is no need to apply the overall heuristic method to maximize the *ROI*.

The problems to be solved had different levels of complexity based on the length of the time horizon. All the models were written in GAMS (Rosenthal, 2008) and solved with the MILP solver CPLEX 12 on a HP Compaq DC5850 desktop PC with an AMD Phenom 8600B, 2.29 GHz triple-core processor, and 2.75 Gb of RAM.

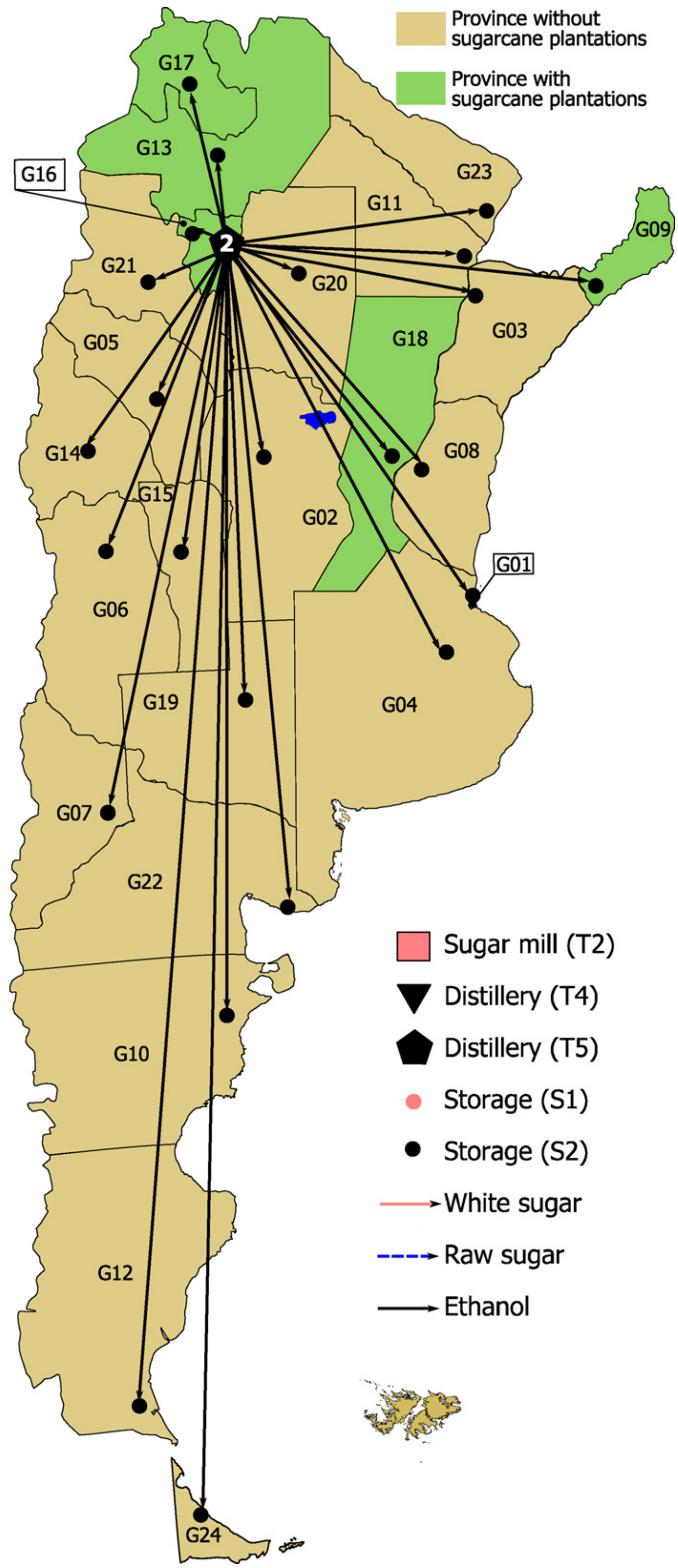

Fig. 16. Configuration of SC under low level of white sugar price.

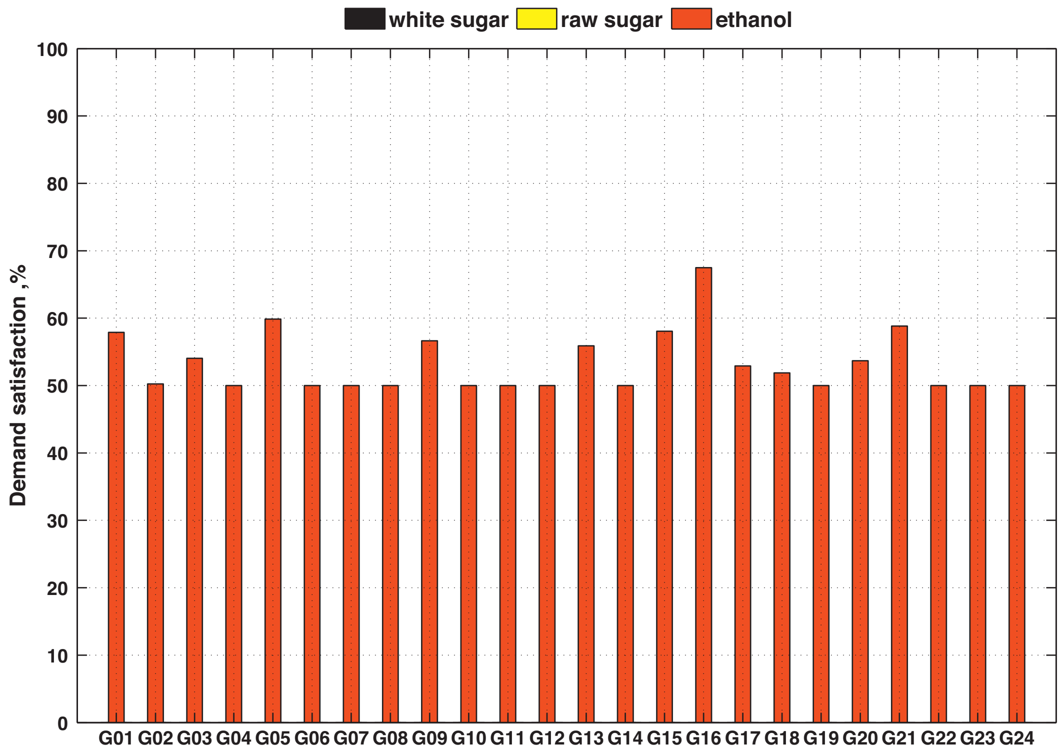

Fig. 17. Demand satisfaction level under low level of sugar price.

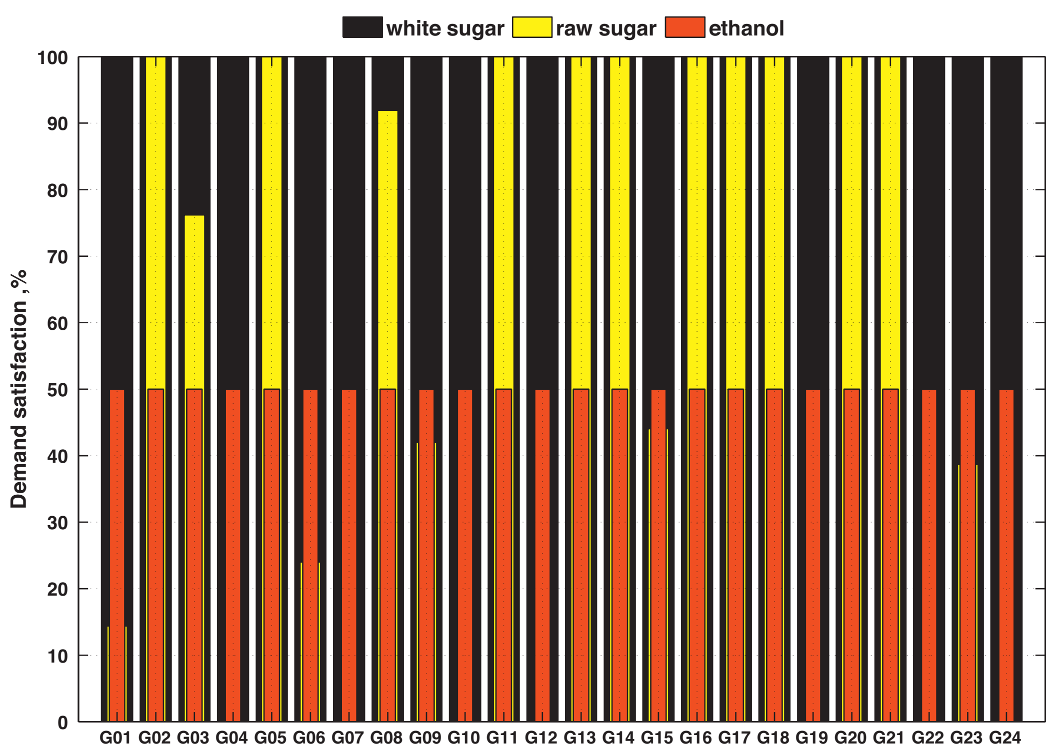

Fig. 18. Demand satisfaction level under low level of ethanol price.

Specifically, the "full space" and "rolling horizon" methods were applied to several problems with time horizons from 2 to 10 years. The upper bound on the capital investment was 1.5 billion $ for all of them.

Figs. 4–12 show the lower and upper bounds provided by the "full space" method as a function of time. In the same figures, we have depicted the solutions calculated by the "rolling-horizon" algorithm using different optimality gaps in the sub-problems. As

Table 10
Capital investments utilized with maximum ROI.

Case	FCI, $	NPV, $	ROI
Base level	1.77×10^9	479,217,967	0.1081
High ethanol price	1.86×10^9	868,467,640	0.1796
Low ethanol price	1.74×10^9	151,473,075	0.0409
High sugar price	1.77×10^9	1,375,331,563	0.2945
Low sugar price	1.10×10^9	−297,129,603	−0.0924
High fuel price	1.77×10^9	455,791,162	0.1031
Low fuel price	1.79×10^9	503,390,346	0.1119

seen, for 2 and 4 time periods, the "full space" method performs better than the rolling horizon, whereas in the remaining cases, there is always at least one tuning of the "rolling-horizon" algorithm that outperforms CPLEX in terms of time (i.e., our algorithm provides solutions with less than 3% of optimality gap in shorter CPU times).

Table 9 provides the optimal solution (i.e., the solution with zero optimality gap) of each instance being solved along with the solutions calculated by the "rolling-horizon" method solving the sub-problems with different optimality gaps. Note that the model can only be solved to global optimality in some cases, whereas in others it is not possible to close the gap to zero after 43,200 of CPU time. Hence, the optimal results refer either to the global optimal solution (in those cases in which such a solution is identified before the time limit is exceeded) or to the solution attained after 43,200 of CPU time. As observed, the "rolling-horizon" algorithm provides in all the cases solutions with low optimality gaps (less than 3%).

5.2. Results for the case study

After proving the computational efficiency of the method, we next used the model to obtain valuable insight on the SC design problem for different plausible scenarios that differ in the cost data. We consider a three-year planning horizon assuming the input data given in Tables 7 and 8. A minimum demand satisfaction level constraint that forces the model to fulfill at least 50% of the ethanol demand in each sub-region was also included. Particularly, we solved the problem for the base case and compared the obtained results with the cases of low (50% below the base case level) and high levels (50% above the base case level) of fuel, sugar and ethanol prices.

For generating solutions close to the maximum *ROI* using our heuristic approach, we divided the interval $[0, \overline{FCI}]$ into 20 subintervals and maximized the *NPV* for different upper bounds on the capital investment that corresponded to the limits of these subintervals. From the obtained solutions, we identified the one with the largest *ROI*. The results of this analysis are presented in Table 10. The resulting *ROI* values for different levels of prices are depicted in Fig. 13.

As shown, ethanol and white sugar prices have the greatest impact on the *ROI* whereas the impact of the fuel price is rather low. The *ROI* and *NPV* take negative values in some cases because the model is forced to attain a minimum demand satisfaction level of ethanol of 50%, even if the production of this product is not profitable. This could be an important result for decision makers, calling for some subsidies or tax relief. Table 11 presents capital and operational expenditures as well as revenues for different prices. As observed, plant, storage and transportation capital costs have similar values. This is due to the small amount of production facilities and large number of storages and transportation links that must be established in the whole territory of Argentina to guarantee a minimum demand satisfaction level for ethanol of 50% in each Argentinean province. Regarding operating cost, landfill expenditures have the smallest share in the operating cost for all cases, and facility operating cost is ten times greater than transportation payments. Among the most profitable cases (high level of white sugar and ethanol price and low level of fuel price) the greatest value of revenue occurs with the increased price of white sugar.

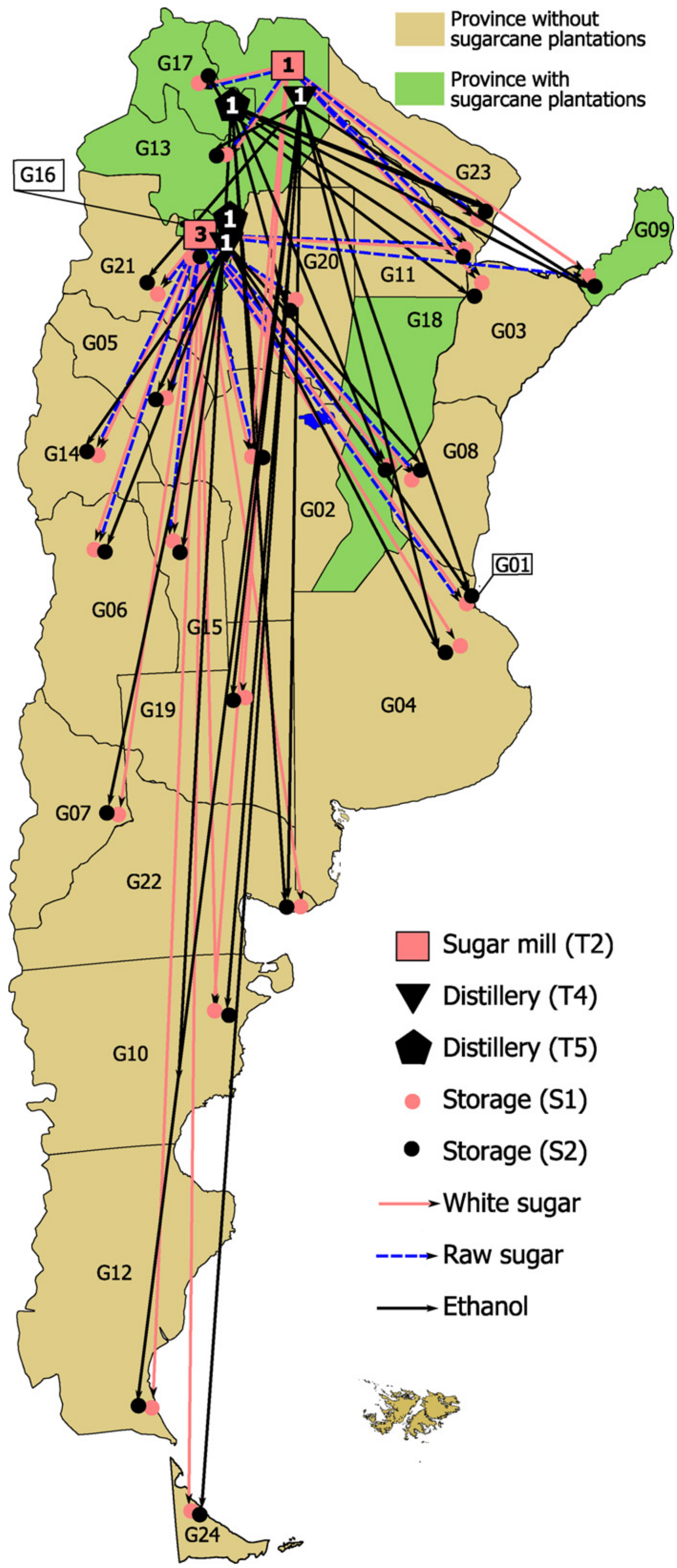

Fig. 19. Configuration of SC under high level of ethanol price.

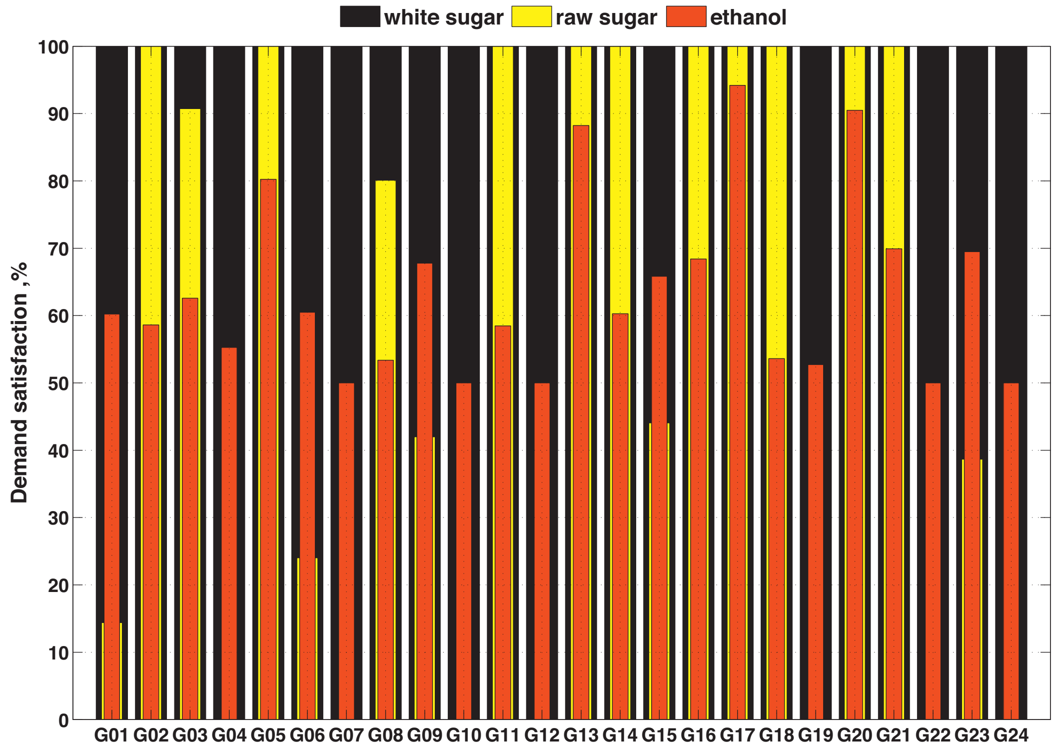

Fig. 20. Demand satisfaction level under high level of ethanol price.

Fig. 14 illustrates the SC configuration for the base case. The absence of sugar cane plantations in most of the Argentinean provinces results in a centralized SC that involves the establishment of production facilities only in Tucumán, Jujuy and Salta, which have inner sources of sugar cane. This configuration is motivated by the large amount of raw materials required for sugar and ethanol production, which would lead to prohibitive transportation cost if the plants were settled far away from the plantations. The resulting demand satisfaction level is shown in Fig. 15. As observed, most of the provinces, except Tucumán and a number of neighboring regions, attain the minimum possible ethanol supply, which indicates the unfavorable situation for ethanol in these regions compared to sugar.

We now show how the model responds to the changes on prices. We illustrate their effect on the optimal SC configuration and the way in which the model can be used to analyze situations that can be encountered in practice. The reduction of sugar price makes the model switch from the combined sugar-ethanol network to an exclusively bioethanol SC with 2 production plants that convert sugar cane directly into ethanol (i.e., distillery T5). The SC configuration for low white sugar price is depicted in Fig. 16. Fig. 17 shows the demand satisfaction level in this case. The need to supply all regions with ethanol and a sugar cane deficit make that ethanol demand is not satisfied completely even in the provinces with their own sugar cane plantations.

The optimal SC configuration for the base level of the product prices remains optimal for the case of the increased sugar price. This happens because the ethanol demand satisfaction constraint results in that sugar cane is converted mainly in ethanol, and sugar factories have not enough amount of raw materials to expand sugar production even under very favorable conditions in the sugar market. Hence, there is no difference in SCs topology and demand satisfaction pattern between the base and high levels of sugar prices.

Fig. 18 depicts the demand satisfaction level under low price of ethanol. It shows that the distilleries produce only the minimum amount of ethanol necessary to attain a 50% of demand satisfaction. For this case the SC configuration is the same as in the base case.

Table 11
Impact of fuel, sugar and ethanol prices on capital and operating costs.

Case	Capital cost, $			Operating cost, $			Revenue,$
	Plants	Storages	Transportation links	Disposal	Facility	Transportation	
Fuel price							
Low level	1,171,823,436	582,485,087	34,160,000	2,482,742	1,478,344,669	173,343,027	3,939,862,440
Base level	1,154,384,264	582,485,087	33,560,000	2,408,644	1,459,984,820	208,941,020	3,905,368,643
High level	1,157,272,391	582,485,087	32,635,000	2,388,156	1,454,908,384	239,818,010	3,895,831,223
Sugar price							
Low level	562,340,000	525,742,524	12,800,000	2,312,061	572,930,061	58,694,929	1,076,400,000
Base level	1,154,384,264	582,485,087	33,560,000	2,408,644	1,459,984,820	208,941,020	3,905,368,643
High level	1,154,384,264	582,485,087	33,560,000	2,408,644	1,459,984,820	208,941,020	5,319,719,295
Ethanol price							
Low level	1,128,335,938	582,210,025	33,560,000	2,297,980	1,432,561,324	207,749,576	3,341,273,840
Base level	1,154,384,264	582,485,087	33,560,000	2,408,644	1,459,984,820	208,941,020	3,905,368,643
High level	1,239,355,122	585,161,472	34,530,000	2,736,842	1,541,324,478	213,160,522	4,672,929,399

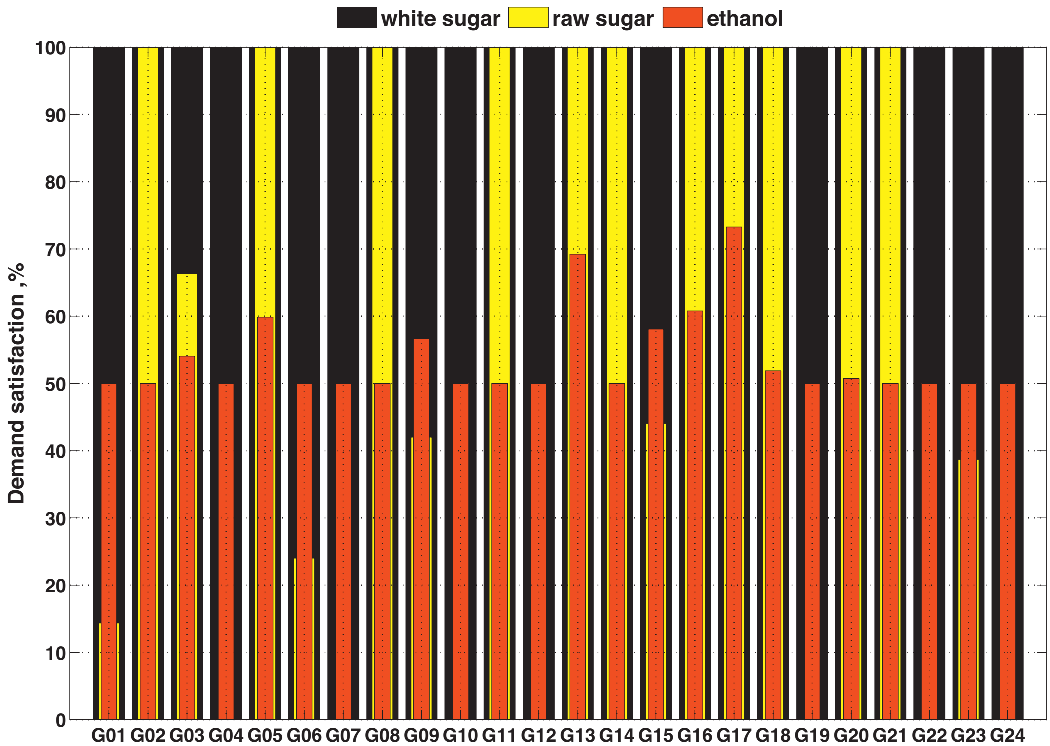

Fig. 21. Demand satisfaction level under high level of fuel price.

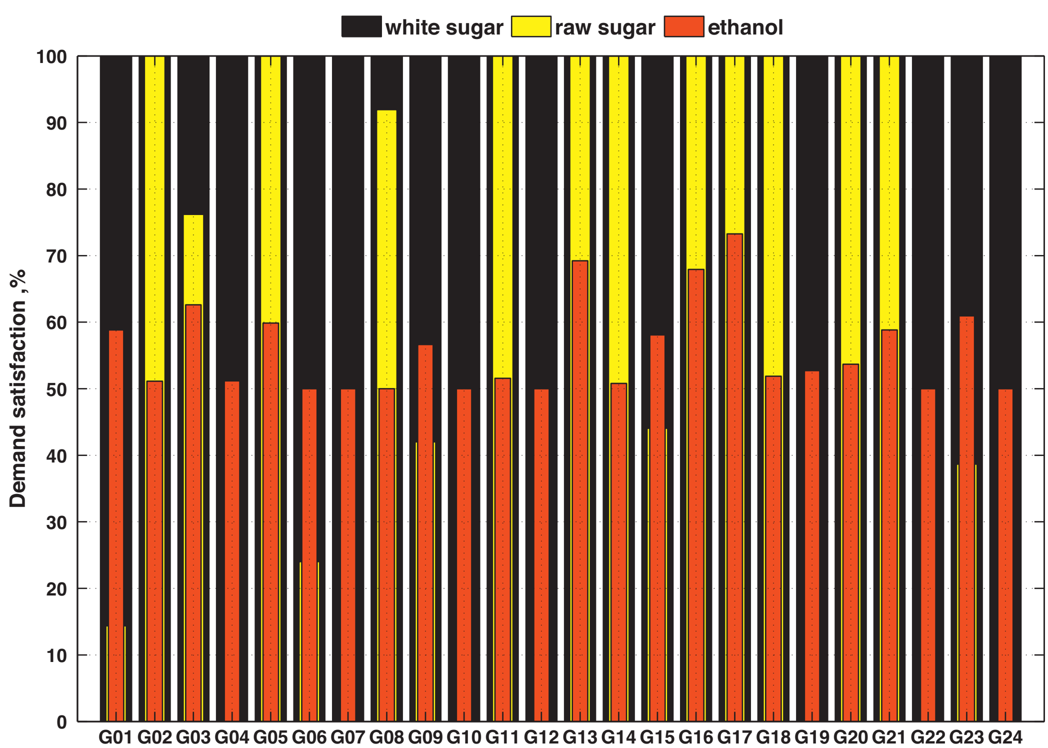

Fig. 22. Demand satisfaction level under low level of fuel price.

On the other hand, a 50% increase in the ethanol price increases the ethanol production and sugar cane consumption and leads to the establishment of a new distillery T5 in Tucumán and a shift from technology T5 to the pair T2–T4 in Salta. The SC configuration under high level of ethanol price is depicted in Fig. 19. Fig. 20 depicts the demand satisfaction level under high level of ethanol price. This plot shows that a 50%-increase of ethanol price results in a significant growth of the demand satisfaction level of ethanol and a shrinkage in sugar production.

With regard to the fuel price, we note that this parameter has the lowest influence on the *NPV*, and its fluctuations mainly result in changes of production capacity but do not affect the supply chain configuration that remains the same as under the base level of prices. Figs. 21 and 22 show the demand satisfaction level under high and low level of fuel price, respectively. As shown, a 50%-decrease of fuel price favors the ethanol production leading to higher ethanol demand satisfaction levels in the distant Argentinean provinces

6. Conclusions

In this work we have addressed the optimal design and planning of integrated sugar/ethanol SCs. The design task was formulated as a mixed-integer programming problem that seeks to maximize the *ROI* and that is approximated by solving a series of MILPs that maximize the *NPV* for different fixed capital investment values. To overcome the large computational burden of solving these MILPs, we proposed an approximation algorithm based on a "rolling horizon" strategy. The capabilities of the proposed mathematical model and solution strategy were shown through a case study based on the Argentinean sugar cane industry.

On the computational side, the "rolling horizon" algorithm provided near optimal solutions (i.e., with less than 3% of optimality gap) in a fraction of the time spent by CPLEX. A sensitivity analysis was also conducted to study the impact that the prices of fuel, ethanol and sugar have on the economic performance and structural configuration of the SC. It was shown that sugar price has the greatest influence on the structure and performance of the integrated ethanol/sugar supply chain. The SC configurations obtained in all the cases are rather centralized, involving the establishment of few production facilities close to the sugar cane plantations. The systematic tool presented in this article aims to facilitate the task of decision makers from the viewpoints of analysis, improvement and optimization of distributed facilities.

Acknowledgments

The authors wish to acknowledge support from the CONICET (Argentina), the Spanish Ministry of Education and Science (DPI2008-04099/DPI, CTQ2009-14420 and ENE2008-06687-C02-01), and the Spanish Ministry of External Affairs (projects A/8502/07, A/023551/09 and HS2007-0006).

Appendix A. Demand data

Sub-region	White sugar	Raw sugar	Ethanol
1st year			
G01	53,644	40,249	60,394
G02	84,280	62,874	108,680
G03	17,848	17,556	31,812
G04	276,077	292,334	342,248
G05	11,647	3038	7860
G06	64,097	11,366	70,309
G07	22,832	5188	19,950
G08	25,634	11,980	38,342
G09	25,365	11,358	30,888
G10	8193	7975	8622
G11	25,587	11,709	31,952
G12	5259	2243	5255
G13	25,889	15,700	33,242
G14	12,074	8440	27,652
G15	17,568	2599	9377
G16	46,365	18,572	79,890
G17	22,286	7753	17,350
G18	62,814	36,975	89,866
G19	10,321	2777	9133
G20	29,559	6875	26,944
G21	10,793	4233	8375
G22	8576	7842	14,485
G23	22,035	5533	19,958
G24	3852	2224	3890
2nd year			
G01	55,458	23,072	107,728
G02	96,928	15,136	66,945
G03	26,914	6959	39,482
G04	690,366	202,816	495,091
G05	13,053	6469	7866
G06	56,074	12,265	62,488
G07	15,706	6748	13,828
G08	24,062	15,149	34,272
G09	36,053	16,195	21,359
G10	17,035	4826	17,895
G11	17,264	10,214	9900
G12	4824	1430	8731
G13	37,737	13,325	23,540
G14	24,968	13,342	26,827
G15	10,067	5931	14,834
G16	24,406	12,927	40,222
G17	18,261	6264	10,412
G18	49,098	34,633	90,737
G19	7760	4845	8755
G20	18,144	5567	28,084
G21	6333	4245	7301
G22	6422	7554	16,559
G23	9620	9249	12,789

Sub-region	White sugar	Raw sugar	Ethanol
G24	3413	1035	2170
3rd year			
G01	59,180	34,173	100,186
G02	88,651	52,658	102,458
G03	32,935	14,046	23,319
G04	618,341	208,166	435,812
G05	10,195	4798	13,662
G06	41,832	27,447	39,005
G07	12,648	6073	15,545
G08	20,107	20,137	35,143
G09	33,125	11,004	43,606
G10	12,678	3800	17,819
G11	19,143	15,705	29,725
G12	4797	2679	4121
G13	32,798	13,881	45,252
G14	15,404	4286	13,037
G15	8660	4931	9591
G16	58,951	14,898	56,302
G17	16,247	8069	14,875
G18	32,433	50,177	100,418
G19	11,106	3864	10,686
G20	20,912	9453	23,443
G21	8316	2965	4763
G22	10,287	6759	14,577
G23	12,048	9136	9165
G24	2971	1430	1782
4th year			
G01	81,041	37,553	106,659
G02	82,537	49,586	142,621
G03	24,431	9003	21,211
G04	452,336	175,920	433,350
G05	10,352	5807	8657
G06	54,661	24,024	20,394
G07	10,726	9004	13,475
G08	22,663	16,499	26,419
G09	49,358	10,011	50,260
G10	12,714	4271	15,163
G11	32,203	11,762	19,996
G12	2335	2065	5685
G13	26,105	20,109	27,515
G14	24,708	7233	23,561
G15	10,183	5466	14,293
G16	36,335	17,611	63,779
G17	25,468	5588	24,870
G18	77,247	48,772	96,126
G19	6889	3701	9886
G20	14,814	8601	13,183
G21	6363	3899	12,756
G22	14,532	4925	20,775

Sub-region	White sugar	Raw sugar	Ethanol
G23	12,865	8755	15,089
G24	4507	1442	548
5th year			
G01	90,436	57,265	45,973
G02	116,148	43,967	75,119
G03	22,863	7206	35,502
G04	527,709	234,621	402,829
G05	12,864	5562	3681
G06	65,022	22,279	49,087
G07	18,420	3426	14,455
G08	36,948	10,959	28,498
G09	23,199	14,015	34,941
G10	12,668	3150	9478
G11	29,923	18,584	43,724
G12	7568	2013	3750
G13	26,388	14,973	27,764
G14	19,210	9292	21,302
G15	10,354	5268	12,824
G16	40,946	26,396	36,171
G17	11,299	7951	12,616
G18	105,312	33,214	102,151
G19	4637	3536	6745
G20	16,971	12,096	26,892
G21	8147	3162	7442
G22	14,457	7242	18,523
G23	14,525	9671	15,193
G24	3442	1514	3022
6th year			
G01	37,848	41,331	61,292
G02	79,839	25,510	85,563
G03	32,855	16,495	34,354
G04	350,540	236,424	655,308
G05	8370	3602	12,712
G06	46,584	26,398	53,566
G07	16,892	7440	23,587
G08	27,271	9900	35,873
G09	22,653	11,804	42,209
G10	8738	6144	17,186
G11	31,398	20,102	7421
G12	5046	3306	6200
G13	24,887	5190	34,655
G14	18,112	8054	22,085
G15	7765	5879	14,333
G16	43,790	18,939	41,081
G17	22,957	8194	17,907
G18	95,156	40,275	103,366
G19	2589	4284	9986
G20	35,656	15,878	25,662
G21	9399	6479	7364
G22	3437	9150	16,379
G23	17,489	8704	15,883
G24	822	2579	2582
7th year			
G01	70,019	35,348	91,848
G02	92,488	54,416	81,006
G03	20,019	19,429	33,165
G04	269,807	115,749	495,853
G05	10,035	2439	12,378
G06	68,584	29,961	43,254
G07	16,636	8694	20,569
G08	13,324	18,070	40,562
G09	28,148	17,246	20,565
G10	5804	6238	12,888
G11	6039	9934	23,552
G12	6515	2658	5132
G13	41,455	13,421	29,086
G14	21,249	8959	15,008
G15	9197	3320	12,552
G16	59,223	16,115	43,151
G17	13,322	6847	26,592
G18	77,359	35,828	87,655
G19	8435	3104	8679
G20	20,236	8522	12,318
G21	7375	575	12,537
G22	12,843	10,765	14,676
G23	20,815	6128	14,248
G24	5294	1569	3082
8th year			
G01	77,585	22,353	75,116
G02	60,651	35,034	93,484
G03	21,598	12,804	27,094
G04	589,705	136,193	672,791
G05	8060	6638	7869
G06	45,772	29,352	43,579
G07	11,444	5579	18,363
G08	27,791	19,832	28,098
G09	23,466	14,446	41,204
G10	17,446	5687	15,949
G11	32,335	12,262	33,185
G12	10,223	1883	4010
G13	25,940	17,717	39,359
G14	14,105	4675	25,762
G15	12,560	6126	12,283
G16	33,300	26,912	47,714
G17	14,549	10,084	23,989
G18	78,210	35,304	115,779
G19	8305	4328	7250
G20	31,068	15,178	24,256
G21	6422	4269	11,348
G22	28,174	5267	13,268
G23	9430	6776	11,364
G24	1810	1816	2790
9th year			
G01	61,168	43,340	40,564
G02	80,033	41,837	115,077
G03	21,797	12,515	28,055
G04	264,304	200,822	505,320
G05	10,181	6137	486
G06	53,675	30,418	67,046
G07	9534	7554	14,329
G08	31,868	14,063	17,189
G09	30,310	12,046	36,014
G10	12,923	7355	10,558
G11	19,663	16,414	48,901
G12	5303	2316	9022
G13	34,221	10,015	23,035
G14	13,204	14,507	15,897
G15	8287	5250	12,466
G16	37,992	12,695	35,650
G17	27,519	10,949	15,357
G18	57,498	52,188	117,496
G19	7123	4435	10,312
G20	17,120	15,918	28,450
G21	6321	4036	12,418
G22	15,344	4745	19,232
G23	11,604	9085	8667
G24	4371	1855	3400
10th year			
G01	32,748	45,740	106,252
G02	37,934	43,025	101,691
G03	32,081	9455	28,496
G04	262,056	214,018	418,869
G05	10,616	4530	8762
G06	56,416	29,465	36,161
G07	7920	9350	14,600
G08	27,751	17,284	30,577
G09	23,619	22,553	29,771
G10	13,940	8626	13,222
G11	11,035	23,497	28,579
G12	8965	3376	9916
G13	33,963	14,753	20,669
G14	9150	8826	25,143
G15	12,940	7330	11,127
G16	51,390	19,344	44,512
G17	15,441	11,464	5051
G18	94,839	9228	99,030
G19	8863	4993	9382
G20	16,774	13,850	29,062
G21	12,074	6657	6582
G22	16,284	10,906	24,103
G23	10,322	7003	11,422
G24	3657	680	3153

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