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Multi-choice mixed integer goal programming optimization for real problems in a sugar and ethanol milling company

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ABSTRACT

Goal Programming (GP) is an important analytical approach devised to solve many real-world problems. The first GP model is known as Weighted Goal Programming (WGP). However, Multi-Choice Aspirations Level (MCAL) problems cannot be solved by current GP techniques. In this paper, we propose a Multi-Choice Mixed Integer Goal Programming model (MCMI-GP) for the aggregate production planning of a Brazilian sugar and ethanol milling company. The MC-MIGP model was based on traditional selection and process methods for the design of lots, representing the production system of sugar, alcohol, molasses and derivatives. The research covers decisions on the agricultural and cutting stages, sugarcane loading and transportation by suppliers and, especially, energy cogeneration decisions; that is, the choice of production process, including storage stages and distribution. The MCMIGP allows decision-makers to set multiple aspiration levels for their problems in which "the more/higher, the better" and "the less/lower, the better" in the aspiration levels are addressed. An application of the proposed model for real problems in a Brazilian sugar and ethanol mill was conducted; producing interesting results that are herein reported and commented upon. Also, it was made a comparison between MCMI GP and WGP models using these real cases.

1. Introduction

The two largest ethanol producers in the world are, in order, the United States of America (USA) and Brazil as showed in Fig. 1. It is used mainly in the USA corn for obtaining ethanol, whereas in Brazil uses sugarcane. In USA sugarcane production is concentrated primarily in the states of Louisiana and Florida, with some production also located in Texas, Hawaii, and Puerto Rico [1].

In Brazil, the total production of sugarcane by the sugar industry in 2009 was 612.21 million ton, a national record, according to the National Supply Company Conab [2]. Ever since, much research has been carried out aiming to improve the sector's operational and financial performance. Colin [3] appointed that Brazil has the largest fleet of vehicles with engines moved by ethanol in the world, and they consumed around a third of the ethanol world's production that was 52,500 million cubic meters in 2007.

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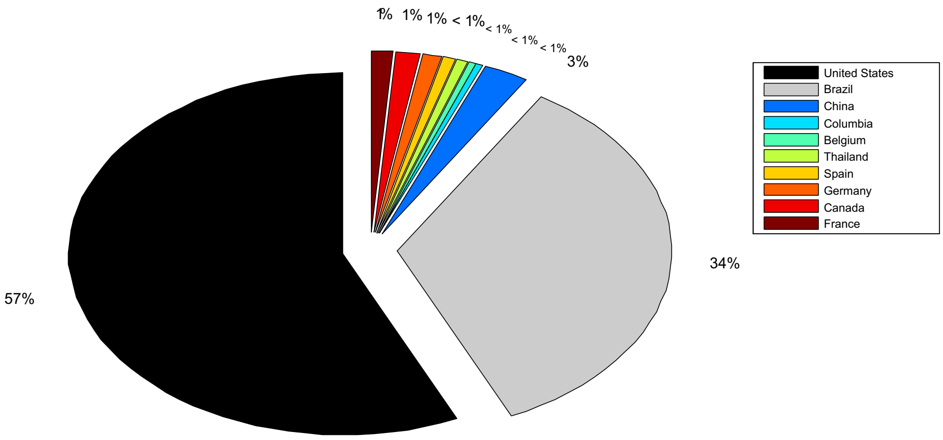

Fig. 1. Fuel ethanol production in 10 leading countries and the world, 2010. Source: [4].

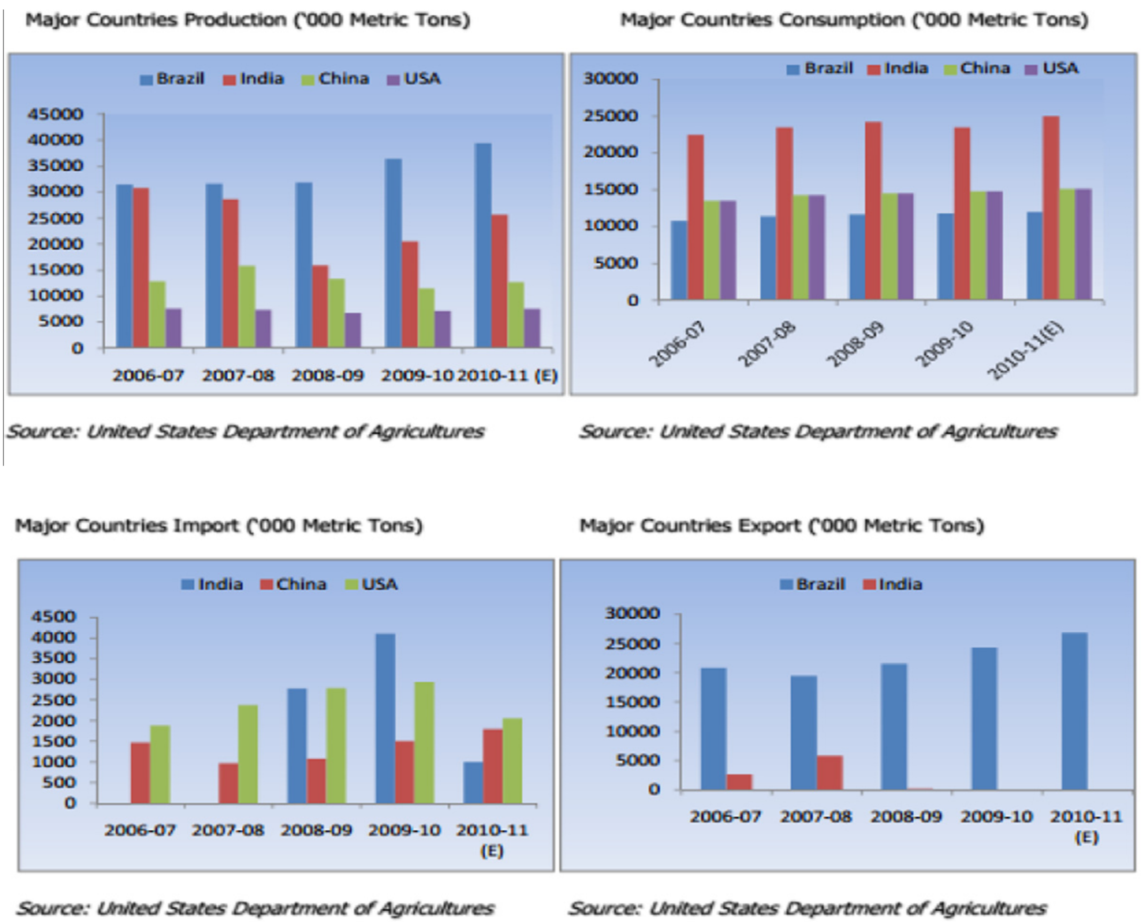

Fig. 2. Global sugar scenario.

The world sugar production for the 2010–11 marketing year was estimated at 161.9 million tons, and the world market sugar prices reached a 30-year high in November/2011. Fig. 2 presents, for the period from 2007 to 2011, global sugar data about major countries production, consumption, import and export. In fact sugar and ethanol are important to global economics, particularly to Brazil where this business sector represents a relevant parcel of its Gross Domestic Product – GDP [5].

In the following we present some research related to the theme and the techniques deployed which have been recently published in scientific journals.

Iannoni and Morabito [6] analyzed the sugarcane receiving procedures in a milling plant using discrete events simulation to evaluate road transport logistics. For more information on discrete event simulations please refer to Montevechi et al. [7].

Kawamura et al. [8] utilized a multi-period linear programming model as support for decisions related to transport products and storage needed by sugar and alcohol producers of a cooperative association. Mathew and Rajendran [9], also using simulation, evaluated the maintenance programming routines of a sugar and ethanol plant, aiming to establish a reasonable break between maintenance shutdowns.

Cock et al. [10] developed a methodology for the selection of sugarcane variety, analyzing the full processing cost of every variety. By using simulation, Higgins and Davies [11] carried out a study aiming to improve the sugarcane transport logistics planning. Yoshizaki et al. [12] made use of a mathematical model in order to solve an alcohol distribution problem in southeast Brazil.

As approached by Jiuping and Liming [13] and Wey and Wu [14], a multi-objective optimization model that utilizes Analytic Network Process (ANP) was proposed. Higgins [15], Higgins et al. [16], Milan et al. [17] and Paiva and Morabito [18] made use of mono-objective optimal design models, applied to sugarcane cutting programming processes, integrated with the provision of transport to crushing plants, also regarding the stage of the sugarcane industrial process.

Bertolini and Bevilacqua [19] combined goal programming (GP) with Analytic Hierarchy Process (AHP) for decisions related to maintenance as Schniederjans and Tim [20] did, combining GP with AHP process and Activity-Based Costing (ABC) for the selection of cost drivers. Gokcen and Erel [21] developed a GP approach for a mixed-model assembly line balancing problem, and they suggested that the GP model provides flexibility to decision makers when evaluating different alternatives. Badri [22] studied the combination of AHP and GP for a global facility location/allocation problem, which offers a systematic approach to location–allocation decision procedures.

Wang and Liang [23] studied the possibility of applying this linear programming to aggregate production planning. This proposed approach uses the strategy of simultaneously minimizing the most possible value of the imprecise total costs, maximizing the possibility of obtaining lower total costs, while minimizing the risk of higher total costs.

Grunow et al. [24] studied how to apply mixed integer optimization in the supply and production of raw sugar. Their planning problem is structured in a hierarchical fashion: (1) cultivation of the farm, (2) harvesting, and (3) dispatching of the harvesting crews and equipment. The corresponding optimization models and the solution procedures are introduced and applied to the case study. For Lisson et al. [25] a basic understanding and appreciation of the key sugarcane physiological processes, and the interactions with other processes in the farming system, is the foundation to many of the decisions made along the value chain of any cropping industry; as the genotype and site selection, the strategic crop management, infrastructure investment, and marketing decisions.

Leung and Chan [26] applied GP in aggregate production planning with resource utilization constraints. Liao [27] proposed a new programming approach to the Multi-Segment Aspiration Level – MSAL problem from the viewpoint of multi-aspiration contribution levels, also known by Multi-Segment Goal Programming – MSGP. Chang [28] proposed a new model known as Multi-Choice Goal Programming – MCGP and compared it with Weight Goal Programming – WGP [29] for small examples. Other related works proposed were: the revised Multi-Choice Goal Programming – RMCGP model [30], the Interval Goal Programming model for S-shaped penalty function [31], a Revised Multi-Segment Goal Programming Model – RMSGP [32], an application of the RMCGP model for a multi-period, multi-stage inventory controlled supply chain model [33], and a multi-coefficients goal programming model [34].

The objectives of this research were to develop and to apply a Multi-Choice Mixed Integer Goal Programming (MCMIGP) model to a real large-scale aggregate production planning problem in a sugar and ethanol milling company, including energy cogeneration, and to compare these results with those obtained by using a WGP model.

The proposed MCMIGP model has the capability to handle realistic situations in an environment of uncertainties and provides another decision tool for aggregate production planning of sugar and ethanol milling companies. In following, we present some characteristics of this research which differ from those available in the referenced literature herein studied:

- Integration between agricultural and industrial phases with the distribution phases in a multi-choice mixed integer goal programming model, supporting decisions during harvest seasons and between harvest periods;
- The application of the proposed MCMIGP for the real large-scale problems of a Brazilian sugar and ethanol mill;
- The generation of scenarios is facilitated, which allows rapid reevaluation assumptions made for each goal;
- The application of the proposed model in mixed integer major problems;
- The generation of new perspectives, enabling the sugar and ethanol company to carry out quick questioning of decisions on the allocation of the production goals established, whereas the monitoring, reassessment and collection of the harvest planning can be performed with greater speed.

This paper is organized into sections. In Section 2, we briefly describe the GP approach. In Section 3, we present a multi-choice goal programming; in Section 4 we comment the research's justification, materials and method. Section 5 refers to the development of the MCMIGP model, and, finally, Section 6 is dedicated to the comparisons between MCMIGP and WGP models and Section 7 we have the conclusions and future research directions, followed by the references.

2. Goal programming approach

One of the benefits of using multi-objective optimization models is the possibility of extracting meaningful information related to the analyzed problem, enabling different analyzes and perceptions, as pointed by Deb [35] and Chang [28].

During the 1970s, Operational Research mathematical models considered orthodox were discredited for the solution of complex management issues Ackoff [36]. A few years later, Ignizio [29] argued that such problems should not be analyzed, aiming only at an optimum solution. On the other hand, it should be seen from the perspective of achieving solutions that would enable the generation of knowledge and learning. GP refers to a multi-objective optimization technique used by decision-makers to solve complex problems, and by those committed to finding solutions which will satisfy most of the objectives [37–39]. GP is an important technique for decision-makers (DMs) to solve multi-objectives decision-making (MODM) problems in finding a set of satisfying solutions [28].

In GP, not all restrictions are rigid or fixed, as in traditional optimization models. In this way, some resources may be over or under used in comparison to what was previously forecasted, depending on the goals set by the decision-makers. There are several alternative approaches to GP, associated with several mathematical programming models, each for specific applications.

The first GP model, known as Weighted Goal Programming (WGP), may be represented by (1)–(4), as proposed by Charnes and Cooper [40] and summarized by Ignizio [29].

Achievement function

$$\min \sum_{i=1}^{n} (\alpha_i d_i^+ + \beta_i d_i^-). \tag{1}$$

Goals and constraints:

$$s.t: \ f_i(X) + d_i^- - d_i^+ = g_i, \quad i = 1, 2, \ldots, n, \tag{2}$$

$$d_i^+, d_i^- \geqslant 0, \quad i = 1, 2, \ldots, n, \tag{3}$$

$$X \in F \ (F \text{ is feasible set}), \tag{4}$$

where parameter α_i and β_i are the weights reflecting preferential and normalizing purposes attached to a positive and negative deviation of ith goal, respectively; $d_i^- = \max(0, g_i - f_i(X))$, $d_i^+ = \max(0, f_i(X) - g_i)$, are, respectively, under- and over-achievements of the ith goal; $f_i(X)$ and g_i are defined as in GP model.

There are many GP models, for example, Lexicographic GP, Minmax GP, Mixed integer goal programming, Binary GP, Integer GP, Minmax GP, Mixed binary GP, and Nonlinear GP, one common characteristic of all the different types of GP models introduced so far is that each goal is formulated in a precise way with coefficients defined by crispy numbers.

For specific purposes, many diversified GP methods have been derived in the literature, as examples of such publications are: [41–44,37,45].

Multi-Choice Goal Programming (MCGP) was developed by Chang [28] to solve Multi-Choice Aspiration Levels (MCAL) problems. According to Chang [28], making decisions is part of our daily lives. However, in some cases, the author believes that there may be situations where the DMs would like to make a decision, taking into account the goal that can be achieved from some specific aspiration levels (i.e., one goal mapping many aspiration levels), and this problem cannot be solved by current GP approaches. This case is a typical MCGP problem and can be expressed as follows:

$$\min \sum_{i=1}^{n} |f_i(X) - g_{i1} \text{ or } g_{i2} \text{ or} \ldots \text{or } g_{im}|, \tag{5}$$

$$\text{s.t. } X \in F \ (F \text{ is a feasible set}), \tag{6}$$

where all variables are defined as in GP.

In this paper the proposed MCMIGP is based on the maximization of $g_{ij}S_{ij}(A)$ (for something more/higher is better in the aspirations levels), as expressed by (7)–(13):

$$\text{Min} \sum_{i=1}^{n} d_i^+ + d_i^- + n_i^+ + n_i^-, \tag{7}$$

$$\text{s.t. } f_i(X) + d_i^+ - d_i^- = \phi_i, \tag{8}$$

$$\phi_i = g_{ij} \cdot S_{ij}, \tag{9}$$

$$\frac{1}{gmax - gmin} \phi_i + n_i^- - n_i^+ = \frac{gmax \text{ or } gmin}{gmax - gmin}, \tag{10}$$

$$S_{ij}(A) \in R_i(x), \quad i = 1, 2, \ldots, n, \tag{11}$$

$$d_i^+, d_i^-, n_i^+, n_i^- \geqslant 0 \quad i = 1, 2, \ldots, n, \tag{12}$$

$$X \in F \ (F \text{ is a feasible set}), \tag{13}$$

where $S_{ij}(A)$ represents a function of binary serial number; $R_i(x)$ is the function of resource limitations; $d_i^+, d_i^-, n_i^+, n_i^-$ are the negative and positive deviation variables, respectively; $\phi_i = g_{ij} \cdot S_{ij}$ is an additional continuous variable; *gmax* and *gmin* are, respectively, lower and upper bound of right-hand side (i.e., aspirations levels).

An alternative formulation would be based on the minimization of $g_{ij} \cdot S_{ij}(A)$ (for something less/lower is better in the aspirations levels).

In this paper, we aimed to give some contributions for the literature of multi-choice goal programming. In other words, we sought to enable its application to the real problems of Brazilian sugar and ethanol mills. The proposed model is covered by 8626 constraints, 1258 binary variables and 36,647 non-negative variables.

The difference of this work in relation to the work of Chang [28] is the application in Mixed Integer Goal Programming problems and optimization of real large-size problems. For more details about multi-choice and multi-segment goal programming please refer to Chang [30,32], Chang and Lin [31], Chang et al. [33,34] and Liao [27].

3. Research method

According to Chang [28], in real-life, many imprecise aspiration levels may exist, and in the sugarcane agro-industry many uncertainties are inherent to the planning process, such as: uncertainties regarding the commodity markets, those related to raw material and the production process.

Quantitative models and methods applied in the planning of the industrial tasks of sugar and ethanol milling companies are not available in the literature, although, such complex activity is held responsible for important decisions as agreed by Paiva and Morabito [18].

Aouni and Kettani [46] commented that throughout the 40 years after GP came to light, it has been applied in several sectors; however, we could not identify any applications in the sugar and ethanol sector. Uría et al. [47] commented that GP is the oldest and the most widely used multiple criteria decision-making (MCDM) approach in a number of cases.

The wide range of fields where GP has been applied is actually impressive. However, no application in sugar and ethanol milling companies has been mentioned. Caballero et al. [48] commented that GP has successfully been applied in many different disciplines. Thus, all these facts indicate that GP is a very interesting decision tool that can be implemented to tackle different kinds of problems.

In this context, the research herein conducted is justified by its relevance and expressiveness to Brazilian sugar and ethanol milling companies, concerning wealth and job generation for the country. The research has also made a scientific contribution by developing new real applications for Multi-Choice GP (MCGP) models.

The research adopted was proposed by Bertrand and Fransoo [49] and Bryman and Bell [50], and may be classified as empirical-descriptive applied to practice, having a quantitative approach and a technical modeling procedure. In order to apply the MIGP model in a real sugar and ethanol plant, research phases were performed:

(a) *Problem identification*. Conceptualization of sugar and ethanol agricultural, industrial and logistics processes. Some milling companies were visited and one was chosen for the MIGP application;
(b) *Data collection*. Data collected internally and company contracts were analyzed;
(c) *Modeling*. An MCMIGP model was developed for the studied company;
(d) *Model solution*. It was utilized GAMS language and CPLEX solver;
(e) *Results validation*. Experts from the company were consulted on the validity of the results.

The Fig. 3 illustrates the questions the research intended to answer concerning the milling processes steps of extraction, production, storage and distribution, with a view to integrate the harvest seasons and the periods between harvest. Such stages and their respective modeling are represented in Section 4.

4. Sugar and ethanol production flow, MCMIGP and WGP models

Paiva and Morabito [18] describe a typical sugar and ethanol industrial process. The final possible products are 7 types of sugar, 2 types of ethanol, and 1 type of molasses. The types of sugar are Crystal, Demerara, Extra, Special, Superior, Very High Polarized (VHP), and Very Very High Polarized (VVHP); and the two types of ethanol are Anhydrous (AEAC) and Hydrated (AEHC).

Fig. 4 illustrates the main operations and the material flow among them: weighting, storage, washing, milling, juice clarification, evaporation, fermentation, distillation, and crystallization. The main losses from the process (washing loss, milling loss and so on) were also included. An important piece of information presented in Fig. 4 is the identification of the process stages, where changes can occur. These stages are TS1, TS2, TM, SJM, and 1-SJM. The several types of products can be produced by a combination of these changing processes.

The aggregate model uses three matrices to prepare the input data for the optimization model:

- Matrix of industrial processes **A**, composed by the quantity of each product p (e.g., sugars, ethanol and molasses) produced by each process k in each period t;

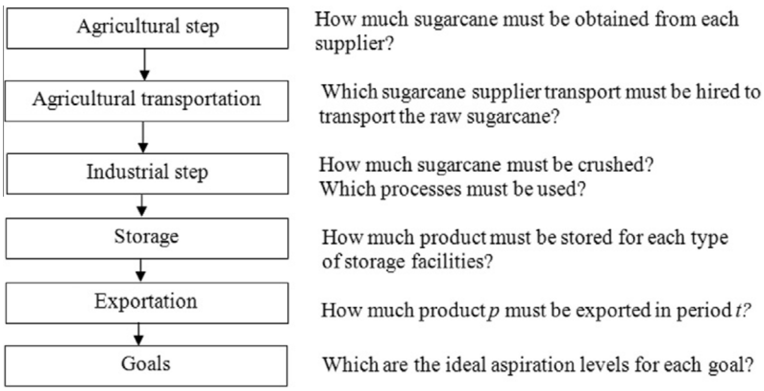

Fig. 3. Research questions.

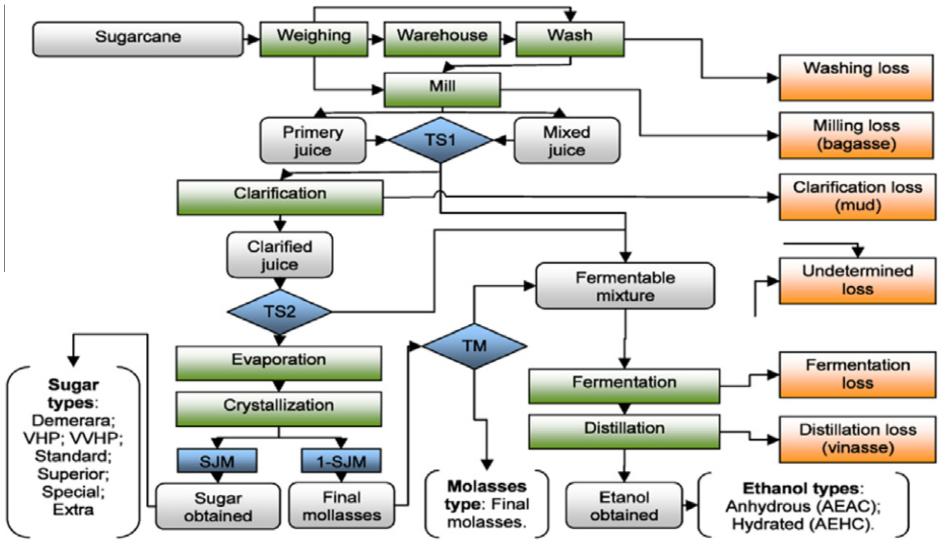

Fig. 4. Sugar and ethanol process flow (source: [18]).

- Matrix of industrial cost **CK**, composed by the cost of using process k in each period t;
- Matrix of agricultural cost **C**, composed by the cost of obtaining sugarcane type m in each period t.
- In this paper, the calculation of matrices **A**, **CK**, and **C** will not be shown. For more details, please consult Paiva and Morabito [18].

4.1. Multi-choice mixed integer goal programming model

The sets, parameters, variables, objective function and constraints of the Multi-Choice Mixed Integer programming (MCMIGP) model are:

Sets	
k	Industrial processes, $k \in K$, $K = \{1, 2, \ldots, 24\}$;
t	Planning periods, $t \in T$, $T = \{1, 2, \ldots, 52\}$;
p	Final products, $p \in P$, $P = \{VHP, VVHP, Crystal, Ethanol\}$.
m	Sugarcane suppliers, $m \in M$, $M = \{prop, rent\}$.
f	Sugarcane transport suppliers, $f \in F$, $F = \{Fprop\}$;
e	Inventory places, $e \in E$, $E = \{Eprop\}$;

(*continued on next page*)

i Destination, $i \in I$, I = {Destination 1, Destination 2, ..., Destination I};
l Distribution of sugar and ethanol, $l \in L$, L = {Transport Provider 1, Transport Provider 2, ..., Transport Provider L};
pp Co-products, $pp \in PP$, PP = {Bagasse, fusel oil}.

Parameters

$M_t^{\min}$ Minimum milling capacity [ton/week];
$M_t^{\max}$ Maximum milling capacity [ton/week];
MC Cash flow available for the season [$];
CT_f Capacity of transport supplier f [ton/week];
α_t Maximum percentage of farmers' sugarcane in period t [%];
$\beta_{f\,t}$ Availability of transport supplier f in period t [%];
φ_t Percentage of available operation time in the plant in period t [%];
γ_t Forecasted efficiency of milling shutdowns in period t [%];
$Cest_{pe}$ Inventory capacity of product p in each place of storage e [ton] for sugar and molasses, or [m^3] for ethanol;
L_{ft} Variable cost of cutting, loading and transporting sugarcane with transport supplier f *in* period t [$/ton];
h_{pe} Variable cost of inventory of product p in each storage place e [$/ton] or [$/m^3];
hs_{pe} Cost of inventory in the after harvesting period of product p in each storage place e [$/ton] or [$/m^3];
DS_{pt} Demand of product p in period t [ton] or [m^3];
DSP_{pit} Demand of product p in period t for destination i [ton] or [m^3];
VP_{pt} Revenue of product p in period t [$/ton] or [$/m^3];
I_{pe0} Initial inventory of product p in each place of storage e [ton] or [m^3];
$Disp_{m0}$ Sugarcane harvesting forecast of sugarcane supplier m [ton];
M'_{m0} Quantity of sugarcane harvested before the first planning period of sugarcane supplier m [ton];
A_{pkt} Matrix of industrial processes yields. Represents each product p yields on each industrial processes k in period t [ton] or [m^3];
CK_{kt} Matrix of industrial costs. Represents each industrial processes k cost in period t [$/ton];
C_{mt} Matrix of agricultural costs. Represents each sugarcane supplier m cost in period t [$/ton].
$Disp_{mt}$ Availability of sugarcane supplier m in period t [ton];
I_{pet} Inventory variable of product p in each place of storage e in period t [ton];
C_{ilt} Shipping cost to destination i using transport provider l, in period t [$];
CAC_{pilt} Shipping cost of products p to destination i using transport provider l in period t [$];
Ib_0 Initial inventory of bagasse [ton];
Fiber_{mt} Cane fiber type m, in period t [%];
Ub_t Humidity of bagasse after milling, in period t [%];
Eb Minimum percentage of inventory bagasse production [%];
EPb Inventory of bagasse for passage harvest [ton];
RC Average yield of boilers [ton vapor/t bagasse];
RCF Average yield the powerhouse [MWh/ton vapor];
CFVAP Fixed consumption of steam in the grinding [ton vapor/ton cane];
CVAP_p Variable consumption of steam served for each product p [ton vapor/ton or m^3];
CFE Fixed consumption of energy in the milling [MWh/ton cane];
CVE_p Variable consumption of energy in each product p [MWh/ton or m^3];
VAPmax Maximum daily production of steam vapor [ton/day];
EGmax Maximum generating daily energy [MWh/day];
VE Value of energy sold [$/MWh];
DAC_{pt} Demand of product p in period t [ton] or [m^3];
DACS_{ppt} Demand of co-product p in period t [ton] or [m^3];
VPS_{ppt} Revenue of co-product p in period t [$];
CS_{ppt} Cost of production of co-product p in period t [ton] or [m^3];
VVPL_{pit} Revenue of product p for destination i in period t [$];
DACS_{pt} Demand of co-product p in period t [ton] or [m^3];
VPS_{pt} Revenue of co-product p in period t [$];
GOAL_{h1} Desired storage cost [$];
GOAL_{h2} Desired raw-material transport cost [$];
GOAL_{h3} Desired raw-material cost [$];
GOAL_{h4} Desired raw-material processing cost [$];
GOAL_{h5} Desired transport provider cost [$];
GOAL_{h6} Desired co-product cost [$];
GOAL_{c1} Desired VHP sugar production [ton];
GOAL_{c2} Desired VVHP sugar production [ton];

$GOAL_{c3}$ Desired Crystal sugar production [ton];
$GOAL_{c4}$ Desired AEHC production [m^3];
$GOAL_{c5}$ Desired energy production [MW].

Decision variables

X_{kt} Process selection variable [no dimension] – decision of using ($X_{kt} = 1$) or not using ($X_{kt} = 0$) process k in period t;
M_t Decision variable of quantity of sugarcane crushed in period t [ton];
M'_{mt} Decision variable of quantity of sugarcane from sugarcane supplier m in period t [ton];
M''_{ft} Decision variable of quantity of sugarcane transport supplier f in period t [ton];
M'''_{kt} Decision variable of quantity of sugarcane crushed by process k in period t [ton];
I_{pet} Inventory level of product p in each storage place e in period t [ton] or [m^3].
XAC_{pilt} Sugar and ethanol quantity of product p to be delivered i to destination i by using transport provider l in period t;
Ib_t Inventory level of bagasse for energy cogeneration in period t [ton];
Mb_t Quantity of bagasse consumed for production of vapor in period t [ton];
VAP_t Quantity of vapor production in period t [ton];
EG_t Quantity of energy cogeneration in period t [MW/h];
EE_t Quantity of energy exported in period t [MW/h].

Auxiliary variables

d^+_{h1} Negative deviation variable of $GOAL_{h1}$ (storage cost goal);
d^-_{h1} Positive deviation variable of $GOAL_{h1}$ (storage cost goal);
d^+_{h2} Negative deviation variable $GOAL_{h2}$ (raw-material transport cost goal);
d^-_{h2} Positive deviation variable of $GOAL_{h2}$ (raw-material transport cost goal);
d^+_{h3} Negative deviation variable of $GOAL_{h3}$ (raw-material goal);
d^-_{h3} Positive deviation variable of $GOAL_{h3}$ (raw-material goal);
d^+_{h4} Negative deviation variable of $GOAL_{h4}$ (raw-material processing cost goal);
d^-_{h4} Positive deviation variable of $GOAL_{h4}$ (raw-material processing cost goal);
d^+_{h5} Negative deviation variable of $GOAL_{h5}$ (transport provider cost goal);
d^-_{h5} Positive deviation variable of $GOAL_{h5}$ (transport provider cost goal);
d^+_{h6} Negative deviation variable of $GOAL_{h6}$ (co-product cost goal);
d^-_{h6} Positive deviation variable of $GOAL_{h6}$ (co-product cost goal);
d^-_{c1} Positive deviation variable of $GOAL_{c1}$ (total VHP sugar production goal);
d^+_{c1} Negative deviation variable of $GOAL_{c1}$ (total VHP sugar production goal);
d^-_{c2} Positive deviation variable of $GOAL_{c2}$ (total VVHP sugar production goal);
d^+_{c2} Negative deviation variable of $GOAL_{c2}$ (total VVHP sugar production goal);
d^-_{c3} Positive deviation variable of $GOAL_{c3}$ (total Crystal sugar production goal);
d^+_{c3} Negative deviation variable of $GOAL_{c3}$ (total Crystal sugar production goal);
d^-_{c4} Positive deviation variable of $GOAL_{c4}$ (total AEHC Production goal);
d^+_{c4} Negative deviation variable of $GOAL_{c4}$ (total AHEC production goal);
n^+_{h1} Deviation variable of over-achievement of ϕ_1;
n^-_{h1} Deviation variable of under-achievement of ϕ_1;
n^+_{h2} Deviation variable of over-achievement of ϕ_2;
n^-_{h2} Deviation variable of under-achievement of ϕ_2;
n^+_{h3} Deviation variable of over-achievement of ϕ_3;
n^-_{h3} Deviation variable of under-achievement of ϕ_3;
n^+_{h4} Deviation variable of over-achievement of ϕ_4;
n^-_{h4} Deviation variable of under-achievement of ϕ_4;
n^+_{h5} Deviation variable of over-achievement of ϕ_5;
n^-_{h5} Deviation variable of under-achievement of ϕ_5;
n^+_{h6} Deviation variable of over-achievement of ϕ_6;
n^-_{h6} Deviation variable of under-achievement of ϕ_6;
n^+_{c1} Deviation variable of over-achievement of ϕ_7;
n^-_{c1} Deviation variable of under-achievement of ϕ_7;
n^+_{c2} Deviation variable of over-achievement of ϕ_8;
n^-_{c2} Deviation variable of under-achievement of ϕ_8;

(*continued on next page*)

n_{c3}^{+}	Deviation variable of over-achievement of ϕ_9;
n_{c3}^{-}	Deviation variable of under-achievement of ϕ_9;
n_{c4}^{+}	Deviation variable of over-achievement of ϕ_{10};
n_{c4}^{-}	Deviation variable of under-achievement of ϕ_{10};
Z_1	Binary variable for aspiration level to goal G_{c1};
Z_2	Binary variable for aspiration level to goal G_{c2};
Z_3	Binary variable for aspiration level to goal G_{c3};
Z_4	Binary variable for aspiration level to goal G_{c4};
Z_5	Binary variable for aspiration level to goal G_{h1};
Z_6	Binary variable for aspiration level to goal G_{h2};
Z_7	Binary variable for aspiration level to goal G_{h3};
Z_8	Binary variable for aspiration level to goal G_{h4};
Z_9	Binary variable for aspiration level to goal G_{h5};
Z_{10}	Binary variable for aspiration level to goal G_{h6};

A MCMIGP is developed to solve the aggregate production-planning problem for the sugar and ethanol milling company. The studied company indicated the following goals:

(1) Variable cost ($\mathrm{GOAL}_{h1;}\,\mathrm{GOAL}_{h2;}\,\mathrm{GOAL}_{h3;}\,\mathrm{GOAL}_{h4;}\,\mathrm{GOAL}_{h5}$);
(2) Production ($\mathrm{GOAL}_{c1;}\,\mathrm{GOAL}_{c2;}\,\mathrm{GOAL}_{c3;}\,\mathrm{GOAL}_{c4}$).

The goals formulations can be expressed as follows:
Goals:

$$(\mathrm{GOAL}_{h1}) \quad \sum_{p\in P}\sum_{e\in E}\sum_{t\in T} h_{pet} I_{pet} = 900,000 \text{ or } 1,000,000, \tag{14}$$

$$(\mathrm{GOAL}_{h2}) \quad \sum_{f\in F}\sum_{t\in T} l_{ft} \mathrm{M}''_{ft} = 26,000,000 \text{ or } 27,000,000, \tag{15}$$

Table 1
The summary proposed model.

Inputs	Outputs	Goals
Agricultural phases		
M_t^{min}		
M_t^{max}		
CT_f	M''_{ft}	
ϕ_t	M_t	GOAL_{h2}
β_{ft}	M'_{mt}	GOAL_{h3}
L_{ft}	$Disp_{mt}$	
$Disp_{m0}$		
M'_{m0}		
C_{mt}		
Industrial phases		
MC_t		
ϕ_t		
γ_t		
$Cest_{pe}$	M'''_{kt}	GOAL_{h1}
hs_{pe}		GOAL_{h4}
DS_{pt}		GOAL_{c1}
V_{pt}		GOAL_{c2}
VC_{pt}	X'''_{kt}	GOAL_{c3}
DACS_{ppt}	I_{pet}	GOAL_{c4}
VPS_{ppt}		
I_{pe0}		
A_{pkt}		
CK_{kt}		
Ib_0	Ib_t	GOAL_{c5}
Fiber_{mt}	EG_t	
Distribution phases		
DSP_{pit}		
CAC_{pilt}	XAC_{pilt}	GOAL_{h5}
VVPL_{pit}		

$$(\mathrm{GOAL}_{h3})\quad \sum_{m\in M}\sum_{t\in T} C_{mt}M'_{mt} = 50,000,000 \text{ or } 52,000,000, \tag{16}$$

$$(\mathrm{GOAL}_{h4})\quad \sum_{k\in K}\sum_{t\in T} CK_{kt}M'''_{kt} = 9,300,000 \text{ or } 9,600,000, \tag{17}$$

$$(\mathrm{GOAL}_{h5})\quad \sum_{p\in P}\sum_{i\in I}\sum_{l\in L}\sum_{t\in T} CAC_{pilt}DSP_{pit} = 1,500,000 \text{ or } 1,800,000, \tag{18}$$

$$(\mathrm{GOAL}_{h6})\quad \sum_{pp\in PP}\sum_{t\in T} DACS\cdot Cs = 1,500,000 \text{ or } 1,800,000, \tag{19}$$

$$(\mathrm{GOAL}_{c1})\quad \sum_{\text{“}vhp\text{”}\in PP}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t = 10,000 \text{ or } 15,000, \tag{20}$$

$$(\mathrm{GOAL}_{c2})\quad \sum_{\text{“}vvhp\text{”}\in PP}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t = 25,000 \text{ or } 30,000, \tag{21}$$

$$(\mathrm{GOAL}_{c3})\quad \sum_{\text{“}crystal\text{”}\in PP}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t = 20,000 \text{ or } 25,000, \tag{22}$$

$$(\mathrm{GOAL}_{c4})\quad \sum_{\text{“}ethanol\text{”}\in PP}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t = 80,000 \text{ or } 85,000, \tag{23}$$

The sugar and ethanol process flow in the company matches with Fig. 4. As such, the same sets, parameters and variables from Section 5 will be adopted. Table 1 summarizes inputs, outputs, and goals from the proposed model.

In addition, some new elements proper to this application, regarding agricultural and logistical processes, were incorporated into MCMIGP model. The achievement function and Constraints are formulated by (25)–(81):

Achievement function

$$\mathrm{Min}\, D = \left\{\begin{array}{l} d^+_{h1} + d^-_{h1} + d^+_{h2} + d^-_{h2} + d^+_{h3} + d^-_{h3} + d^+_{h4} + d^-_{h4} + d^+_{h5} + d^-_{h5} + d^-_{c1} + d^+_{c1} \\ +d^-_{c2} + d^+_{c2} + d^-_{c3} + d^+_{c3} + d^+_{c4} + d^-_{c4} + d^-_{r} + d^+_{r} + n^+_{r} + n^-_{r} + n^+_{c1} + n^-_{c1} \\ +n^+_{c2} + n^-_{c2} + n^+_{c3} + n^-_{c3} + n^+_{c4} + n^-_{c4} + n^+_{h1} + n^-_{h1} + n^+_{h2} \\ +n^-_{h2} + n^+_{h3} + n^-_{h3} + n^+_{h4} + n^-_{h4} + n^+_{h5} + n^-_{h5} + n^+_{11} + n^-_{11} + d^-_{c5} + d^+_{c5} \end{array}\right\}. \tag{25}$$

Constraints

– Constraint (26) represents the contribution margin of all agro-industrial, industrial and distribution phases of the milling company.

$$\sum_{p\in P}\sum_{k\in K}\sum_{t\in T} VP_{pt}A_{pkt}M_t + \sum_{p\in P}\sum_{i\in I}\sum_{t\in T} \mathrm{VVPL}_{pit}\cdot DSP_{pit} + \sum_{pp\in PP}\sum_{t\in T} DACS\cdot Vps - \left(\begin{array}{l} +\sum_{m\in M}\sum_{t\in T} C_{mt}\cdot M'_{mt} + \sum_{p\in P}\sum_{t\in T} h_{pe}\cdot I^+_{pet}\sum_{k\in K}\sum_{t\in T} CK_{k_t}\cdot M'''_{kt} \\ +\sum_{f\in F}\sum_{t\in T} L_{ft}\cdot M''_{ft} + \sum_{p\in P}\sum_{t\in T} hs_{pe}\cdot I_{pe}\cdot \text{“}T\text{”} \\ +\sum_{pilt}\sum_{p\in P}\sum_{i\in I}\sum_{l\in L}\sum_{t\in T} \mathrm{CAC}_{pilt}DSP_{pilt} + \sum_{pp\in PP}\sum_{t\in T} DACS\cdot Cs \end{array}\right) \geqslant MC. \tag{26}$$

– Eq. (27) is the small bucket constraint in each period t, which means that only one process can be used in each week;

$$\sum_{k\in K} X_{kt} = 1 \quad \forall t\in T. \tag{27}$$

– Eq. (28) is the inventory balance of final product p for destination i in period t;

$$\sum_{e\in E} I_{pet} = I_0 + \sum_{e\in E} I_{pet_{-1}} + \sum_{k\in K} A_{pkt}M_t - DAC_{pt} \quad \forall t\in T. \tag{28}$$

– System (29) are the compatibility constraints over variables M'_{mt}, M'''_{kt}, M''_{ft} and M_t, which means that this is a single-stage model.

$$\begin{aligned}
&\sum_{m\in M} M''_{mt} = \sum_{f\in F} M''_{ft} \quad \forall t\in T,\\
&\sum_{f\in F} M''_{ft} = \sum_{k\in K} M'''_{kt} \quad \forall t\in T,\\
&\sum_{k\in K} M'''_{kt} = M_t \quad \forall t\in T.
\end{aligned} \tag{29}$$

– System (30) are the availability constraints over sugarcane m in each period t.

$$\begin{aligned}
&Disp_{mt} = Disp_{m\,t-1} - M'_{m\,t-1} \quad \forall m\in M,\ \forall t\in T,\\
&Disp_{m\,t-1} - M'_{m\,t-1} \geqslant M'_{mt} \quad \forall m\in M,\ \forall t\in T.
\end{aligned} \tag{30}$$

– Eq. (31) is the constraint of utilization of all available sugarcane in the harvesting season; it assumes that if part of the sugarcane planted is not available for the present season, this amount is not taken into account by the model.

$$\sum_{m\in M} disp_{mt} = \sum_{t\in T} m_t. \tag{31}$$

– Inequality (32) is the capacity constraint for the quantity of sugarcane crushed in each period t.

$$M_t^{\min}\frac{\varphi_t}{100}\frac{\gamma_t}{100} \leqslant M'_t \leqslant M_t^{\max}\frac{\varphi_t}{100}\frac{\gamma_t}{100} \quad \forall t\in T. \tag{32}$$

– Inequality (33) restricts the amount of sugarcane supplied by farmers and by the mill owners (prop and rent, respectively) that is going to be crushed in period t, the two main reasons to use such constraint are: modeling the periods that farmers and mill owners accept for supplying their sugarcane; reserving a minimum amount of sugarcane that is going to be supplied by the mill farms (prop and rent), which represents the amount required by the agronomic planners considering the consequences of changing time of harvest and other constraints involved in the harvesting scheduling of paddocks.

$$M'_{prop} + M'_{rend} \leqslant \phi_t M_t \quad \forall t\in T. \tag{33}$$

– Inequality (34) is the capacity constraint for the quantity of sugarcane transported by mill owned transport system f in period t.

$$M''_{ft} \leqslant \frac{\beta_{ft}}{100}\cdot\frac{\gamma_t}{100}\cdot CT_f \quad \forall f\in F,\ \forall t\in T. \tag{34}$$

– Constraint (35) imposes that the quantity of sugarcane processed by process k in period $t(M'''_{kt})$ should be zero if process k is not used in period k ($X_{kt} = 0$), and it should be less than or equal to $M^{\max}$ otherwise ($X_{kt} = 1$).

$$M'''_{kt} \leqslant M_t^{\max} X_{kt} \quad \forall k\in K,\ \forall t\in T. \tag{35}$$

– Inequality (36) is the constraint of inventory capacity of product p in each storage place e in period t.

$$I_{pet} \leqslant Cest_{pe} \quad \forall p\in P,\ \forall e\in E,\ \forall t\in T. \tag{36}$$

– Eq. (37) calculates the total VHP sugar production.

$$\sum_{\text{“}vhp\text{”}\in P}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t + d^-_{c1} - d^+_{c1} = \phi_7. \tag{37}$$

– Eqs. (38) and (39) are complementary to Eq. (36).

$$\phi_7 = 10{,}000z_1 + 15{,}000(1-z_1), \tag{38}$$

$$\frac{1}{5000}\phi_7 - n^+_{c1} + n^-_{c1} = 3. \tag{39}$$

– Eq. (40) calculates the total VVHP sugar production.

$$\sum_{\text{“}vvhp\text{”}\in P}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t + d^-_{c2} - d^+_{c2} = \phi_8. \tag{40}$$

– Eqs. (41) and (42) are complementary to Eq. (40).

$$\phi_8 = 25{,}000z_2 + 30{,}000(1-z_2), \tag{41}$$

$$\frac{1}{5000}\phi_8 - n^+_{c2} + n^-_{c2} = 6. \tag{42}$$

– Eq. (43) calculates the total Crystal sugar production.

$$\sum_{\text{“}crystal\text{”}\in P}\sum_{k\in K}\sum_{t\in T} A_{pkt}M_t + d^-_{c3} - d^+_{c3} = \phi_9. \tag{43}$$

– Eqs. (43)–(45) are complementary to Eq. (41).

$$\phi_9 = 20,000z_3 + 25,000(1 - z_3), \tag{44}$$

$$\frac{1}{5000}\phi_9 - n_{c3}^+ + n_{c3}^- = 5. \tag{45}$$

– Eq. (46) calculates the total AEHC production in m^3.

$$\sum_{\text{"ethanol"} \in P}\sum_{k \in K}\sum_{t \in T} A_{pkt}M_t + d_{c4}^- - d_{c4}^+ = \phi 10. \tag{46}$$

– Eqs. (47) and (48) are complementary to Eq. (47).

$$\phi_{10} = 80,000z_4 + 85,000(1 - z_4), \tag{47}$$

$$\frac{1}{5000}\phi_{10} - n_{c4}^+ + n_{c4}^- = 17. \tag{48}$$

– Eq. (49) calculates the total storage cost in period t.

$$\sum_{p \in P}\sum_{e \in E}\sum_{t \in T} h_{pet}I_{pet} - d_{h1}^+ + d_{h1}^- = \phi_1. \tag{49}$$

– Eqs. (50) and (51) are complementary to Eq. (50).

$$\phi_1 = 900,000z_5 + 1,000,000(1 - z_5), \tag{50}$$

$$\frac{1}{100,000}\phi_1 + n_{h1}^+ - n_{h1}^- = 9. \tag{51}$$

– Eq. (52) calculates the total raw-material transport cost from suppliers.

$$\sum_{f \in F}\sum_{t \in T} l_{ft}\mathrm{M}_{ft}'' + d_{h2}^- - d_{h2}^+ = \phi_2. \tag{52}$$

– Eqs. (53) and (54) are complementary to Eq. (51).

$$\phi_2 = 26,000,000z_6 + 27,000,000(1 - z_6), \tag{53}$$

$$\frac{1}{1,000,000}\phi_2 + n_{h2}^+ - n_{h2}^- = 26. \tag{54}$$

– Eq. (55) calculates the total raw-material cost from supplier m.

$$\sum_{m \in M}\sum_{t \in T} \mathrm{C}_{mt}M_{mt}' + d_{h3}^- - d_{h3}^+ = \phi_3. \tag{55}$$

– Eqs. (56) and (57) are complementary to Eq. (54).

$$\phi_3 = 50,000,000z_7 + 52,000,000(1 - z_7), \tag{56}$$

$$\frac{1}{2,000,000}\phi_3 + n_{h3}^+ - n_{h3}^- = 25. \tag{57}$$

– Eq. (58) calculates the total raw-material processing cost.

$$\sum_{k \in K}\sum_{t \in T} CK_{kt}M_{kt}''' + d_{h4}^- - d_{h4}^+ = \phi_4. \tag{58}$$

– Eqs. (59) and (60) are complementary to Eq. (57).

$$\phi_4 = 9,300,000z_8 + 9,600,000(1 - z_8), \tag{59}$$

$$\frac{1}{300,000}\phi_4 + n_{h4}^+ - n_{h4}^- = 31. \tag{60}$$

– Inequality (61) represents the maximum storage capacity for sugars (Crystal, VHP, VVHP) in period t.

$$BF_{pe} \leqslant 10,000 \quad \forall p \in P,\ \forall e \in E. \tag{61}$$

– Eq. (62) calculates the total raw-material processing cost of the process k.

$$\sum_{p \in P}\sum_{i \in I}\sum_{l \in L}\sum_{t \in T} CAC_{pilt}DSP_{pit} - d_{h5}^+ + d_{h5}^- = \phi_5. \tag{62}$$

– Eqs. (63) and (64) are complementary to Eq. (61).

$$\phi_5 = 1,500,000 z_9 + 1,800,000(1 - z_9), \tag{63}$$

$$\frac{1}{300,000}\phi_5 + n_{h5}^+ - n_{h5}^- = 5. \tag{64}$$

– Eq. (65) calculates the total raw-material processing cost of the process k.

$$\sum_{pp \in PP}\sum_{t \in T} DACS \cdot Cs - d_{h6}^+ + d_{h6}^- = \phi_6. \tag{65}$$

– Eqs. (66) and (67) are complementary to Eq. (61).

$$\phi_6 = 1,500,000 z_{10} + 1,800,000(1 - z_{10}), \tag{66}$$

$$\frac{1}{300,000}\phi_{10} + n_{h6}^+ - n_{h6}^- = 5. \tag{67}$$

The followed are the restrictions pertaining to calculations of energy cogeneration.

– Eq. (68) modeling the balance of stock of bagasse in period t;

$$Ib_t = Ib_{t-1} + \sum_m \left(M'_{mt} \frac{\mathrm{Fiber}_{mt}}{1 - \mathrm{UB}_t} \right) - \mathrm{Mb}_t \quad \forall t \in T. \tag{68}$$

– Eq. (69) modeling of safety stock of bagasse in period t;

$$Ib_t \geqslant Ib_{t-1} + \sum_m \left(M'_{mt} \frac{\mathrm{Fiber}_{mt}}{1 -' UB_t} \right) \mathrm{EB} \quad \forall t \in T. \tag{69}$$

– Eq. (70) regulates the passage of bagasse stock;

$$Ib_{``T"} \geqslant \mathrm{EPb} \quad \forall t \in T. \tag{70}$$

– Eq. (71) modeling the production of vapor according to the quantity of bagasse consumed in period t;

$$\mathrm{Mb}_t \mathrm{RC} = \mathrm{VAP}_t \quad \forall t \in T. \tag{71}$$

– Eqs. (72) and (73) modeling the balance of high and low vapor pressure of any industrial plant in period t;

$$\mathrm{VAP}_t \geqslant \sum_{k \in K} \mathrm{M}'''_{kt} \cdot \mathrm{CFVAP} + \frac{\mathrm{EG}_t}{\mathrm{RCF}} \quad \forall t \in T, \tag{72}$$

$$\sum_{k \in K} \mathrm{M}'''_{kt} \cdot \mathrm{CFVAP} + \frac{\mathrm{EG}_t}{\mathrm{RCF}} \geqslant \sum_{k \in K}\sum_{p \in P} \mathrm{CVAP}_p \cdot \mathrm{A}_{pkt} \mathrm{M}'''_{kt} \quad \forall t \in T. \tag{73}$$

– Eq. (74) modeling the amount of surplus energy that can be consumed in each period t.

$$\mathrm{EG}_t - \left(\sum_{k \in K} \mathrm{CFEM}'''_{kt} + \sum_{k \in K}\sum_{p \in P} \mathrm{CVAP}_p \mathrm{A}_{pkt} \mathrm{M}'''_{kt} \right) = \mathrm{EE}_t \quad \forall t \in T. \tag{74}$$

– Eqs. (75) and (76) modeling the constraints of production capacity of vapor and electricity in period t.

$$\mathrm{VAP}_t \leqslant \mathrm{VAPMax} \cdot \mathrm{nu}_t \quad \forall t \in T, \tag{75}$$

$$\mathrm{EG}_t \leqslant \mathrm{EGMax} \cdot \phi_t \quad \forall t \in T. \tag{76}$$

– Eq. (77) modeling the total energy cogeneration.

$$\sum_{t \in T} EG_t + d_{c5}^- - d_{c5}^+ = 30,000. \tag{77}$$

– Eq. (78) presents the non-negativity and integrality constraints.

$$\begin{aligned}
&X_{kt} \in \{0,1\};\\
&Z_1, Z_2, \ldots, Z_{10} \in \{0,1\};\\
&M \geqslant 0; \quad M'_{mt} \geqslant M''_{ft} \geqslant 0; \quad M'''_{kt} \geqslant 0;\\
&Disp_{mt} \geqslant 0; \quad I_{pet} \geqslant 0; \quad XAC_{pilt} \geqslant 0;\\
&d_{h1}^+, d_{h1}^-, d_{h2}^+, d_{h2}^-, d_{h3}^+, d_{h3}^-, d_{h4}^+, d_{h4}^-, d_{h5}^+, d_{h5}^-, d_{h6}^+, d_{h6}^-, d_{c1}^+, d_{c1}^-, d_{c2}^+, d_{c2}^-, d_{c3}^+, d_{c3}^-, d_{c4}^+, d_{c4}^{-\,-} \geqslant 0;\\
&n_{h1}^+, n_{h1}^-, n_{h2}^+, n_{h2}^-, n_{h3}^+, n_{h3}^-, n_{h4}^+, n_{h4}^-, n_{h5}^+, n_{h5}^-, n_{h6}^+, n_{h6}^-, n_{c1}^+, n_{c1}^-, n_{c2}^+, n_{c2}^-, n_{c3}^+, n_{c3}^-, n_{c4}^+, n_{c4}^- \geqslant 0;\\
&\phi_1, \phi_2, \phi_3, \phi_4, \phi_5, \phi_6, \phi_7, \phi_8, \phi_9, \phi_{10} \geqslant 0\\
&\forall p \in P,\ \forall t \in T,\ \forall k \in K,\ \forall l \in L,\ \forall m \in M,\ \forall f \in F,\ \forall i \in I.
\end{aligned} \tag{78}$$

The WGP model applied to the same problem would have the objective function (79), same constraints as MCMIGP, without (38), (39), (41)–(45), (47), (48), (50), (51), (53), (54), (56), (57), (59), (60), (63), (64), (66), (67), because these excluded constraints are all related to the uncertainties (ϕ_i) over right-hand side coefficients considered by MCMIGP.

$$\operatorname{Min} D = \left\{ \begin{array}{l} d_{h1}^{+} + d_{h1}^{-} + d_{h2}^{+} + d_{h2}^{-} + d_{h3}^{+} + d_{h3}^{-} + d_{h4}^{+} + d_{h4}^{-} + d_{h5}^{+} + d_{h5}^{-} + d_{c1}^{-} + d_{c1}^{+} \\ +d_{c2}^{-} + d_{c2}^{+} + d_{c3}^{-} + d_{c3}^{+} + d_{c4}^{+} + d_{c4}^{-} + d_{r}^{-} + d_{r}^{+} + d_{c5}^{-} + d_{c5}^{+} \end{array} \right\}. \tag{79}$$

5. Applications and comparisons of the MCMIGP and WGP models to a Real Company Mill

The company mill (CM) that was studied is a sugar and ethanol producer situated in southeast Brazil. CM is able to produce various types of sugar: VHP, VVHP, Crystal; one main type of ethanol fuel: sugarhouse co-product such as molasses; and some sub-products such as filter mud, bagasse, vinasse and fuel oil. In a typical harvesting season, CM crushes 1.4 million tons of sugarcane and produces 120 thousand tons of sugar and 90 thousand m^3 of ethanol.

The present case study was conducted using data from the 2008/2009 harvesting seasons and, between harvests, the aim was to analyze whether the proposed model could improve the corresponding aggregate production planning. For reasons of confidentiality, we are working with proportional economic values in compliance with the CM's conditions to provide the data for this research.

For both MCMIGP and WGP models applications, an Intel (Core i7) 1.252 GHz processor, with 8 GB RAM and max turbo frequency and operational system from Microsoft 64 bits was used. The model was solved using the modeling language GAMS 23.6.2 with the optimization solver CPLEX 12.2.1. The total time consumed for MCMIGP model optimization was 2.85 h, and the total time for WGP model optimization was 1.9 h.

The optimal solution for MCMIGP is shown in Table 2. Interesting data to be observed in Table 2 are the differences obtained in columns (a) and (b); this comparison shows the relative gap in both results. Analyzing Table 2, it can be observed that the MCMIGP model produced more ethanol than sugar, especially AEHC ethanol (difference of 2.91% from the CM result). It was also observed that VVHP sugar was favored in detriment to Crystal and VHP sugar.

Another observation concerns the overall industrial efficiency: both plans involved almost the same values (0.66% divergent), which means that, technically, the MCMIGP model solution is close to the CM plant's reality. Notwithstanding, the most important result exposed in Table 2 is the total variable revenue result. Analyzing this important issue, we note that the model total variable revenue is 9.59% higher than the result obtained by the CM plant for this season.

Also, we obtained: $Z_1 = Z_2 = Z_3 = Z_4 = Z_5 = Z_6 = Z_8 = Z_9 = Z_{10} = 0$, $Z_7 = 1$ that is all these goals, associated with $\phi_1 = 1{,}000{,}000$; $\phi_2 = 26{,}000{,}000$; $\phi_3 = 50{,}000{,}000$; $\phi_4 = 9{,}600{,}000$; $\phi_5 = 1{,}800{,}000$; $\phi_6 = 1{,}500{,}000$; $\phi_7 = 15{,}000$; $\phi_8 = 30{,}000$; $\phi_9 = 25{,}000$; $\phi_{10} = 85{,}000$. From the results we realize that goals c_1, c_2, c_3, c_4, and h_4 has reached the aspirations levels exactly.

In the sequence, the same problem was formulated and solving using WGP model, considering $G_{h1} = 900{,}000$; $G_{h2} = 26{,}500{,}000$; $G_{h3} = 50{,}000,\ 000$; $G_{h4} = 9{,}500{,}000$; $G_{h5} = 1{,}700{,}000$; $G_{h5} = 1{,}500{,}000$; $G_{c1} = 15{,}000$; $G_{c2}=\ 30{,}000$; $G_{c3} = 25{,}000$). The results are in Table 3.

Analyzing Table 3, it can be observed that the WGP model indicates that it must produce more ethanol than sugar, especially AEHC ethanol (difference of 0.75% from the CM result), and that VVHP sugar was favored in detriment to Crystal and VHP sugar. Another observation concerns the overall industrial efficiency: both plans involved almost the same values (0.44% divergent), which means that, technically, the WGP model solution is also close to the CM plant's reality.

Notwithstanding, the most important result exposed in Table 3 is the total variable revenue result. Analyzing this important issue, we note that the WGP model's total variable revenue is 8.29%, higher than the result obtained by the CM plant for this season.

From the WGP model results, we realized that goal G_{c1} has a negative value (-983) under aspiration level 15,000; goal G_{c2} has a positive value (+420) over aspiration 30,000; goal G_{c3} has a positive value (+1956) over aspiration level 25,000; goal G_{c4} has a positive value (+684) over aspiration level 85,000. The total deviations in percentage by goals Gc were 3.48%. About the goals of the variable costs, the following results obtained: goal G_{h1} has a positive value (+1682) over aspiration level 900,000;

Table 2
Result comparison between CM planners and the MC-GP model.

	(*a*) MC-GP	(*b*) Company Mill 2007/2008	$[(a-b)/b]$ Difference
Crystal	26,956 (ton)	–	–
VHP	15,000 (ton)	–	–
VVHP	30,200 (ton)	–	–
Total sugar	72,156 (ton)	68,000 (ton)	6.11%
AEHC	86,818 (m^3)	84,360 (m^3)	2.91%
Final industrial efficiency	90.9 (%)	90.3 (%)	0.66%
Contribution margin	10,122,578 ($)	9,236,894 ($)	9.59%
Energy	29.000 (MW)	28.500 (MW)	1.75%

Table 3
Result comparison between CM planners and the WGP model.

	(a) WGP	(b) Company Mill 2007/2008	$[(a-b)/b]$ Difference
Crystal	26,956 (ton)	–	–
VHP	14,017 (ton)	–	–
VVHP	30,406 (ton)	–	–
Total sugar	71,379 (ton)	68,000 (ton)	4.97%
AEHC	84,991 (m^3)	84,360 (m^3)	0.75%
Final industrial efficiency	90.7 (%)	90.3 (%)	0.44%
Contribution margin	10,022,578 ($)	9,236,894 ($)	8.29%
Energy	28.887 (MW)	28.500 (MW)	1.3%

goal G_{h2} has a positive value (+176,000) over aspiration level 26,500,000; goal G_{h3} has a positive value (+767,000) over aspiration level 50,000,000; goal G_{h4} has reached the aspiration level of exactly 9,500,000; G_{h5} has a positive value (+47,350) over aspiration level 1,700,000; goal G_{h6} has reached the aspiration level of exactly 1,500,000. In short, the total deviation, in percentage, for goals G_h was 5.17%.

It is interesting to note that the solution of MCMIGP model is better than that of the WGP model's solution because is more balanced on the nine goals. In fact, according to Chang [28], the more the aspiration levels, the better the solutions found in the proposed MCMIGP model.

These results encourage the use of the MCMIGP model to support decisions in the aggregate production planning. Managers could adopt a planning strategy with decreasing horizon, firstly solving the model by considering all weeks of the harvesting season and then, as soon as each week's data are made available, by taking into account only the remaining weeks until the end of the season. With this strategy, the aggregate production planning and analysis become routine and the impact of data uncertainty is minimized.

Another issue, concerning the application of this aggregate production-planning model is the fact that the agronomic consequences of the changing weather upon harvest from each of the sugarcane sources are not directly taken into consideration, as we consider the sugarcane quality as an input parameter of the model. That impact could be minimized with the application of the MCMIGP model.

6. Conclusions and future research directions

This paper presents MCMIGP and WGP models for aggregate production planning, distribution, and energy cogeneration of a Sugar and Ethanol Milling Company. Both models were applied to a real aggregate production-planning problem in a Brazilian Sugar and Ethanol Milling Company (MC), and the MCMIGP performed better.

The MCMIGP model provides useful insights for decision makers, helping them to better comprehend the variables and important issues that are being considered. The MCMIGP provides a robust and feasible way for solving multi-objectives decision-making (MODM) problems, which involves either-or-choice/multi-choice of aspirations levels.

The MCMIGP model application can be viewed as a decision aid to help administrative managers to make better decisions, regarding problems of sugar and ethanol mills. The superiority of the proposed model was observed through a real application to solve problems of sugar and ethanol milling companies. The total time consumed during optimization MCMIGP was superior to the time consumed by the WGP model. This occurred because the MCMIGP model includes a greater number of binary variables and constraints.

All goals (variable cost and total production of product p) were fully optimized by MCMIGP model, and the MC's staff validated results. It is important to note that all questions in Fig. 3 can be fully answered:

(a) How much raw-material must be obtained from each supplier, see system (29);
(b) Which raw-material transport supplier must be hired to transport the raw sugarcane, see system (29). Observe that, in the case presented in this paper, only one transport supplier was considered;
(c) How much raw-material must be crushed, see system (29).
(d Which raw-material processing must be used, see constraint (33).
(e) How much of each product must be stored, see constraint (28).
(f) What shall be the type of storage, see constraint (36). However, in the case presented in this paper, only one type of storage was considered.
(g) How much product p must be exported in period t, see constraint (62).
(h) Which is the ideal aspirations level for each goal (represented by the values of variables $\phi_1, \phi_2, \ldots, \phi_{10}$).

Besides those actions, it may be suggested to the Sugar and Ethanol Milling Company that they should adopt a decreasing planning horizon strategy, as explained in the end of previous section, in order to minimize the impact of data uncertainty. Finally, the impact of a changing weather over the quality of sugarcane during harvest can be minimized with the application of the MCMIGP model.

The results of this study are promising and encourage other research efforts. Here are a few suggestions for future researches:

– Analyzing the effects of uncertainties in the input parameters of the model by Fuzzy Sets, Sensitivity Analysis or other techniques [51–53];
– Analyzing the application of response surface methodology in the industrial costs matrix [54].

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References

[1] M.E. Salassi, J.B. Breaux, C.J. Naquim, Modeling within-season sugarcane growth for optimal harvest system, Agric. Syst. 73 (2002) 261–278.
[2] Conab (National Supply Company): Technical Report. <http://www.conab.gov.br/>, 2010 (accessed 23.04.10).
[3] E. Colin, Mathematical programming accelerates implementation of agro-industrial sugarcane complex, Eur. J. Oper. Res. 199 (2009) 232–235.
[4] F.O. Licht, World Ethanol Biofuels Rep. 8 (16) (2010) 328.
[5] United States Department of Agricultures USDA. <http://www.moneycontrol.com/news_html_files/broker_report/2011/Feb0511-7050211.pdf>, 2012 (accessed 10.11.12).
[6] A.P. Iannoni, R.A. Morabito, Discrete simulation analysis of a logistics supply system, Transp. Res. Part E: Logist. Transp. Rev. 42 (2006) 191–210.
[7] J.A.B. Montevechi, A.F. de Pinho, L. Fabiano, F.A.S. Marins, Application of design of experiments on the simulation of a process in an automotive industry, in: Proceedings of the Winter Simulation Conference 2007.
[8] M.S. Kawamura, D.P. Ronconi, H. Yoshizaki, Optimizing transportation and storage of final products in the sugar and ethanol industry, Int. Trans. Oper. Res. 13 (5) (2006) 425–439.
[9] J. Mathew, C. Rajendran, Scheduling of maintenance activities in a sugar industry using simulation, Comput. Ind. 21 (1993) 331–334.
[10] J.H. Cock, C.A. Luna, A. Palma, The trade-off between total harvestable production and concentration of the economically useful yield component: cane tonnage and sugar content, Field Crops Res. 67 (2000) 257–262.
[11] A.J. Higgins, I. Davies, A simulation model for capacity planning in sugar cane transport, Comput. Electron. Agric. 47 (2005) 85–102.
[12] H.T.Y. Yoshizaki, A.R.N. Muscat, J.L. Biazzi, Decentralizing ethanol distribution in southeastern Brazil, Interfaces 26 (6) (1996) 24–34.
[13] X. Jiuping, Y. Limming, A class of expected value multi-objective programming problems with rough coefficients, Math. Comput. Modell. 50 (2009) 141–158.
[14] V.M. Wey, K.Y. Wu, Using ANP priorities with goal programming in resource allocation in transportation, Math. Comput. Modell. 46 (2007) 100–985.
[15] A.J. Higgins, Scheduling of road vehicles in sugar transport: a case study at an Australian sugar mill, Eur. J. Oper. Res. 170 (2006) 987–1000.
[16] A.J. Higgins, G. Antony, I. Davies, G. Sandel, D. Prestwidge, B.A. Andrew, Framework for integrating a complex harvesting and transport system for sugar production, Agric. Syst. 82 (2004) 99–115.
[17] E.L. Milan, S.M. Fernandez, L.M.P. Aragones, Sugar cane transportation in Cuba, a case study, Eur. J. Oper. Res. 174 (2006) 374–386.
[18] R.P.O. Paiva, R. Morabito, An optimization model for the aggregate production planning of a Brazilian sugar and ethanol milling company, Ann. Oper. Res. 169 (2009) 117–130.
[19] M. Bertolini, M. Bevilacqua, A combined goal programming – AHP approach to maintenance selection problem, Reliab. Eng. Syst. Saf. 91 (2006) 839–848.
[20] M.J. Schniederjans, G. Tim, Using the analytic hierarchy process and multi-objective programming for the selection of cost drivers in activity-based costing, Eur. J. Oper. Res. 100 (1997) 72–80.
[21] H. Gokcen, E. Erel, A goal programming approach to mixed-model assembly line balancing problem, Int. J. Prod. Econ. 48 (1997) 177–185.
[22] M.A. Badri, Combining the analytic hierarchy process and goal programming for global facility location–allocation problem, Int. J. Prod. Econ. 62 (1999) 237–248.
[23] R.C. Wang, T.F. Liang, Applying possibilistic linear programming to aggregate production planning, Int. J. Prod. Econ. 98 (2005) 328–341.
[24] M. Grunow, H.O. Günter, R. Westinner, Supply optimization for the production of raw sugar, Int. J. Prod. Econ. 110 (2007) 224–239.
[25] S.N. Lisson, N.G. Inman-Bamber, M.J. Robertson, B.A. Keating, The historical and future contribution of crop physiology and modelling research to sugarcane production systems, Field Crops Res. 92 (2005) 321–335.
[26] S.C.H. Leung, S.S.W. Chan, A goal programming model for aggregate production planning with resource utilization constraint, Comput. Ind. Eng. 56 (2009) 138–141.
[27] C.N. Liao, Formulating the multi-segment goal programming, Comput. Ind. Eng. 56 (2009) 1053–1064.
[28] C.-T. Chang, Multi-choice goal programming, Int. J. Manage. Sci. 35 (2007) 389–396.
[29] J.P. Ignizio, Goal Programming and Extensions, Lexington Books, Lexington, MA, 1976.
[30] C.-T. Chang, Revised multi-choice goal programming, Appl. Math. Modell. 32 (2008) 2587–2595.
[31] C.T. Chang, T.C. Lin, Interval goal programming for S-shaped penalty function, Eur. J. Oper. Res. 199 (2009) 9–20.
[32] C.-T. Chang, Revised multi-choice goal programming for multi-period, multi-stage inventory controlled supply chain model with popup stores in Guerrilla marketing, Appl. Math. Modell. 58 (2010) 3586–3598.
[33] C.-T. Chang, H.-M. Chen, Z.-Y. Zhuang, Revised multi-segment goal programming: percentage goal programming, Comput. Ind. Eng. 63 (2012) 1235–1242.
[34] C.-T. Chang, H.-M. Chen, Z.-Y. Zhuang, Multi-coefficients goal programming, Comput. Ind. Eng. 62 (2012) 616–623.
[35] K. Deb, Multi-Objective Optimization using Evolutionary Algorithms, John Wiley & Sons, 2001.
[36] R.L. Ackoff, Resurrecting the future of operational research, J. Oper. Res. Soc. 30 (1979) 189–199.
[37] M. Tamiz, D. Jones, E. El-Darzi, A review of goal programming and its applications, Ann. Oper. Res. 58 (1995) 39–53.
[38] M. Tamiz, D.F. Jones, C. Romero, Goal programming for decision making: an overview of the current state-of-the-art, Eur. J. Oper. Res. 111 (1998) 569–581.
[39] J.L. Cohon, Multiobjective Programming and Planning, Dover, 2005.
[40] A. Charnes, W.W. Cooper, Management Model and Industrial Application of Linear Programming, vol. 1, Wiley, New York, 1961.
[41] D.F. Jones, M. Tamiz, Expanding the flexibility of goal programming via preference modelling techniques, Int. J. Manage. Sci. 23 (1995) 41–48.
[42] A. Biswas, B.B. Pal, Application of fuzzy goal programming technique to land use planning in agricultural system, Int. J. Manage. Sci. 33 (2005) 391–398.
[43] R.K. Pati, P. Vrat, P. Kumar, A goal programming model for paper recycling system, Int. J. Manage. Sci. 36 (2008) 405–417.
[44] P. Linares, C. Romero, Aggregation of preferences in an environmental economics context: a goal-programming approach, Int. J. Manage. Sci. 30 (2002) 89–95.

[45] C. Romero, A general structure of achievement function for a goal programming model, Eur. J. Oper. Res. 153 (2004) 675–686.
[46] B. Aouni, O. Kettani, Goal programming model: a glorious history and a promising future, Eur. J. Oper. Res. 133 (2001) 225–231.
[47] M.V.R. Uría, R. Caballero, F. Ruiz, C. Romero, Meta-goal programming, Eur. J. Oper. Res. 136 (2002) 422–429.
[48] R. Caballero, T. Gómez, F. Ruiz, Goal programming: realistic targets for the near future, J. Multi-Criteria Decis. Anal. (2009). http://dx.doi.org/10.1002/mcda.442.
[49] J.W.M. Bertrand, J.C. Fransoo, Operations management research methodologies using quantitative modeling, Int. J. Oper. Prod. Manage. 22 (2002) 241–264.
[50] A. Bryman, E. Bell, Business Research Methods, second ed., Oxford University Press, 2007.
[51] D.D. Wu, Y. Zhang, D. Wu, D.L. Olson, Fuzzy multi-objective programming for supplier selection and risk modeling: a possibility approach, Eur. J. Oper. Res. 200 (2010) 774–787.
[52] B. Aouni, J.M. Martel, A. Hassaine, Fuzzy goal programming model: an overview of the current state-of-the Art, Microelectron. Reliab. 33 (2009) 63–80.
[53] B. Bankian-Tabrizi, K. Shahanaghi, M.S. Jabalameli, Fuzzy multi-choice goal programming, Appl. Math. Modell. 36 (2012) 1415–1420.
[54] R.B. Kazemzadeh, M. Bashiri, A.C. Atkinson, R. Noorossana, A general *framework* for multiresponse optimization problems based on goal programming, Eur. J. Oper. Res. 189 (2008) 421–429.