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Harvest Planning in the Brazilian Sugar Cane Industry via Mixed Integer Programming

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Resumo. Este trabalho foca no planejamento do cultivo e colheita de cana-de-açúcar que determina o melhor momento para colher cada um dos talhões, maximizando o lucro total pelo teor de açúcar extraído da cana. O planejamento é separado em dois horizontes: tático e operacional. O planejamento tático considera uma safra inteira, na média sete meses. O planejamento operacional varia entre sete e trinta dias. Os dois problemas são resolvidos como modelos de programação inteira-mistas. Desigualdades válidas são propostas para tornar a formulação mais forte. Técnicas de pré-processamento e soluções iniciais obtidas heuristicamente são passadas para o resolvedor de programação inteira para facilitar a resolução. Os experimentos são feitos sobre instâncias artificiais e reais fornecidas por um produtor de cana-de-açúcar no Brasil. Um caso de estudo ilustra os benefícios do planejamento proposto.

Palavras-chave: PO na agricultura, Colheita de cana-de-açúcar, Programação inteira-mista, Desigualdades válidas.

Abstract. This work addresses harvest planning problems that arise in the production of sugar and alcohol from sugar cane in Brazil. The planning is performed for two planning horizons, tactical and operational planning, such that the total sugar content in the harvested cane is maximized. The tactical planning comprises the entire harvest season that averages seven months. The operational planning considers a horizon from seven to thirty days. Both problems are solved by Mixed Integer Programming. The tactical planning is well handled. The model for the operational planning extends the one for the tactical planning and is presented in detail. Valid inequalities are introduced and three techniques are proposed to speed up finding quality solutions. These include preprocessing by grouping and filtering the distance matrix between fields, hot starting with construction heuristic solutions, and dividing and sequentially solving the resulting MIP program. Experiments are run over a set of real world and artificial instances. A case study illustrates the benefits of the proposed planning.

Keywords: OR in agriculture, Sugar cane harvesting, Mixed integer programming, Valid inequalities.

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Contents

1 Introduction

Sugar cane is one of the most important commodities in the world (FAO, 2012), commonly being further processed to sugar or agro fuel. With more than 420 million tons of harvested sugar cane in the year 2005, Brazil is by far the largest producer of this crop worldwide, followed by India, China and Thailand. Among all agricultural commodities produced in Brazil, sugar cane is its most produced measured in biomass and its fourth most lucrative. Internationally, sugar cane production is a highly competitive market. Recent studies such as the ones by Higgins et al. (2007) and Bezuidenhout and Baier (2009) indicated great opportunities to improve the value chain and reduce costs in the operational planning to remain competitive.

On the level of sugar cane harvest planning, there are commonly two major planning objectives. First, the highest possible profit in terms of quantity and quality of the harvested cane, respecting certain industrial, social and environmental constraints. Such constraints include limited cutting capacities as well as constant cane supply at the mills. Second, the reduction of all costs involved. The profit strongly depends on the sugar content when harvesting the cane. Due to limited resources and constraints, harvesting at each field at its maturation peak is commonly not feasible.

Based on the experience of a large Brazilian sugar producer, this work aims at providing mathematical models for tactical and operational harvest planning, focusing on the objective and constraints pointed out above. In the following, we explain the problem in more detail and outline the structure of this paper.

1.1 Problem description

The problem, denoted by the *Sugar Cane Cultivation and Harvest Problem (SCHP)* throughout this work, is now described. One of its most important decisions is the moment to harvest the plantation fields. Clearly, it is desirable to harvest each field at the peak of its sugar content, as the sugar content indicated by the *percentage of sucrose in the sugar cane (Pol)* and the *reduced sugar*, vary as the cane grows. The cane at each field possesses a certain initial age and can only be cut within a given interval of its age.

Cutting crews. Sugar cane is harvested by cutting crews, chopping down the stems but leaving the roots to re-grow in time for the following harvest. Even though most cutting crews are mechanical, federal working agreements oblige Brazilian harvesting companies to contract a certain minimum of manual harvesting, i.e., a group of human workers. One of the Brazilian sugar cane companies involved in this research currently holds five mechanical and one manual harvesting crews, which is referred to be a representative proportion. Each cutting crew may be eligible to cut only a certain subset of the fields. Cutting crews may not work every day and work a limited time at each day. Individual characteristics of each cutting crew must be taken into account: minimum and maximum cutting capacities, transportation speed as well as cutting and relocation costs.

Transportation. Once the sugar cane is cut, the harvest is immediately transported to the industrial sector, i.e. the sugar cane mills. In Brazil, transportation is mostly performed by trucks (a single mill is known which additionally uses river shipping). Figure 1 exemplifies routes for cutting and transportation. Cutting crews commonly follow a certain route from one field to another harvesting the cane. Transportation crews commute between the fields and the mills. Each transportation crew possesses individual properties such as a transport capacity, speed and cost. Exactly one transportation crew must be assigned to each field that will be harvested.

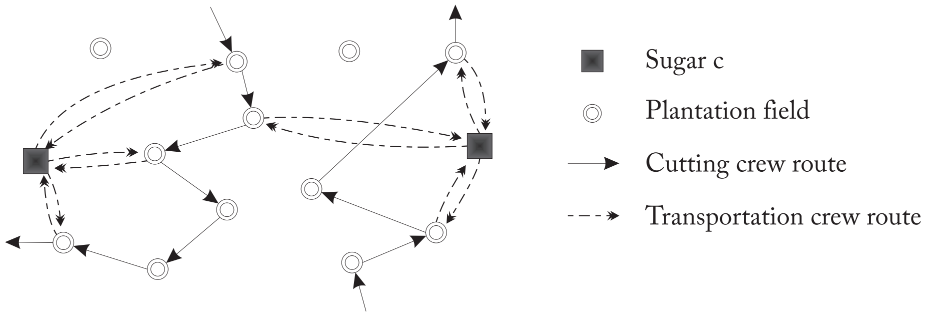

Figure 1: Example routes for cutting transportation crews

Sugar cane mills. In the mills, the sugar cane is crushed and the cane juice is extracted, being further processed either to ethanol or sugar, also denoted by the *total recoverable sugar* (*ATR*, *Açúcar Total Recuperável*, in Brazil). The mills operation is one of the most important constraints as they must not interrupt sugar cane processing. Minimum and maximum process capacities must be respected for each mill. Plantation fields that have been selected for harvesting are assigned to exactly one sugar cane mill. Furthermore, the processed sugar cane must contain a certain minimum quantity of fiber used to generate electricity to operate the mills. Some mills may not be available during certain periods (e.g., for maintenance). This is reflected in the capacities for such mills given in the input data.

Growth regulators. Some sugar cane varieties allow the use of growth regulators to anticipate its harvest. In general, such products slow down the growing process of the cane mass, whereas the growth of the sucrose within the cane is not affected. Their influence of growth regulators on these properties can be fairly well predicted based on past data recorded at mills. Growth regulators can only be applied on fields with certain cane varieties and when the cane reaches minimum age. One of the most important and most difficult tasks to maximize the total profit is thus to determine the ideal moment to apply growth regulators and to harvest each field.

Vinasse application. A side effect of the alcohol distillation process is a residual liquid called vinasse. Vinasse is a corrosive contaminant that contains high levels of organic matter, potassium, calcium and moderate amounts of nitrogen and phosphorus. However, vinasse is an efficient fertilizer, thus its application to harvested plantation fields has become common practice. To allow for frequent application, a sufficiently large field area must be harvested within certain time periods.

1.2 Outline

This work is organized as follows. Section 2 reviews the literature that is most related to this subject. Section 3 focuses on the tactical and operational planning. The Mixed Integer Programming (MIP) models for both planning are discussed in Section 4. Section 5 deals with the problem instances, computational experiments and further techniques applied to the operational problem in order to facilitate its solution. Finally, Section 6 illustrates the benefits of the proposed operational planning on a case study.

2 Literature review

Methods of Operations Research have been applied to the agricultural sector since more than five decades. One of the first reviews of literature applying decision support tools to agriculture was given by Glen (1987). A recent survey by Ahumada and Villalobos (2009) reviews the main contributions in the agri-food supply chain.

In the context of sugar cane, there has been a considerable effort from the operations research society, including, among others, value chain optimization, harvest and crew scheduling and prediction of sugar cane performance indicators. References in the context of supply chains of sugar cane production systems can be found in a recent review of Bezuidenhout and Baier (2009). In the following, we focus on works that deal with mathematical models related to our field of study, namely tactical and operational harvest planning.

Guise and Ryland (1969) present a tactical mid- to long-term planning to maximize profits for sugar cane producers. Their quadratic MIP model aims at finding the best crushing periods for sugar cane mills, considering all involved costs such as harvesting, transportation, storing and crushing. Higgins (1999) also presents a non-linear MIP model for strategic to tactical harvest planning. As one of the main decisions of the presented model is when to harvest the cane, his work is strongly related to the tactical planning presented in this work. Higgins (2006) focuses on a related subject, the operational planning of sugar cane transportation, considering different transportation modes such as by trucks and railway. The MIP model presented by Paiva and Morabito (2008) handles the tactical planning for an industrial application in Brazil. The planning covers an entire harvesting season and handles sugar cane transportation, crushing and process selection within the mills. Sugar cane to be crushed is assumed to be delivered by a number of suppliers. For operational planning, Lopez Milan et al. (2006) present a MIP model for harvesting and transportation. Decisions involve the allocation of harvesting and transportation crews to fields, while a constant supply at the mills has to be guaranteed given a set of harvesting resources. A given harvesting plan for one month is broken down into separated days. The planning then focuses on the detailed intra-day planning and emphasizes the cane arrival times at the mills. Several other works such as the one by Semenzato (1995) focus on more specific objectives to schedule activities involved in the harvesting process. The cited work aims at minimizing the time between burning and processing the sugar cane to prevent its transformation into ethanol.

Finally, it should be pointed out that harvesting in the forestry sector also covers several aspects related to the scheduling of harvesting crews in the sugar cane industry. In the next section, we define the complete problem and discuss in more detail the main differences to the works cited above.

3 Tactical and Operational Harvest Planning

The Pol and reduced sugar values for each cane variation are one of the most important performance indicators to select the best moment for a field's harvest. However, even though growth and maturation profiles can be estimated based on past data, an exact prediction for a long period such as twelve months is not possible. Dividing the entire planning into a *tactical planning (TP)* and an *operational planning (OP)* has proved to be an effective approach. First, the TP performs the planning for the entire planning horizon, i.e. up to a complete harvest season, suggesting decisions for each week. Afterwards, the total planning time is divided into smaller periods of up to 30 days. The OP is then performed for each of these sub periods, using the decisions of the TP (i.e., where and which quantities to harvest in that time period) as input data and making decisions for each day. Note that, in sugar cane harvesting, it is very common that the operational planning solution cannot be exactly executed in practice as suggested. In this case, all fields that should have been harvested, but were not, are projected into the next operational planning period. If the deviation is too high, an entire re-planning on the tactical level may be performed.

Works such as the ones by Guise and Ryland (1969), Higgins (1999) and Paiva and Morabito (2008) model tactical planning. The here presented TP differs from these works mostly by the set of decisions made within the planning, emphasizing the optimal harvest moment of the cane while considering the application of growth regulators and limited resources. On the level of the operational planning, Lopez Milan et al. (2006) present an approach similar to ours, but with hourly planning units to cover exactly one day. As the sugar content in cane often significantly varies throughout an entire month, the here presented OP focuses on the sequence in which the fields are harvested during the month. The work of Lopez Milan et al. (2006) is therefore rather complementary to our OP.

The OP suggests routes of harvesting crews, allows cutting activities at the same field that may exceed one day and takes into account the time to relocate from one field to another. Table 1 resumes the main differences between both planning.

	TP	OP
Planning horizon	up to 12 months	7 to 30 days
Decision time units	weekly	daily
Cutting crews	yes	yes
Cutting crew harvest sequence	no	yes
Transportation crews	yes	no
Use of growth regulators	yes	no
Vinasse application	yes	yes

Table 1: Principal differences between the TP and OP

Both the TP and the OP maximize the total profit measured by the quantity of ATR. The ATR is computed as a weighted sum of the reduced sugar and the Pol, taking into consideration the cane type and maturation grade. Both planning determine, amongst others, for each of their decision time units (i.e., weeks for the TP and days for the OP):

- the plantation fields that should be harvested and the corresponding cutting crews.
- the mill where the cane of each harvested field should be processed.
- where to apply which type and quantity of vinasse.

A final solution must satisfy the following constraints:

- the sugar cane must be harvested within a given interval of eligible age.
- the minimum and maximum capacities of cutting crews are respected.
- sugar cane must be transported to and processed in the mill during the same time unit as it is cut. The processed cane quantity in each mill must satisfy its minimum and maximum processing demands.
- mills must produce a certain minimum quantity of fiber, given by a percentage within the processed sugar cane.

- in all planning units, a sufficiently large area must be harvested in order to allow for applying vinasse on the free areas.

3.1 Tactical planning

The TP supports the planning for a total planning horizon of up to one harvest season. In Brazil, this corresponds to an average of seven months. It may be applied to shorter periods, usually in the re-planning during a running season. It is assumed that each of the fields can be harvested within one week. In addition to the previously presented decisions, the TP also determines the following for each week, subject to certain constraints:

- the transportation crews that carry the cut sugar cane to the mills. Each field is assigned to exactly one transportation crew. All transportation crews have a maximum capacity of cane that they can carry.
- the growth regulators that shall be applied and the fields at which the products shall be applied. Such products can be applied only during certain intervals of the sugar cane's age. After its application, the sugar cane must be harvested within a given number of weeks.

3.2 Operational planning

The OP performs a detailed planning for a time horizon of up to 30 days. Based on the tactical decisions for the chosen time period, the OP may redefine assignments between cutting crews, fields and mills. Valid assignments are informed in the input data. Decisions about the application of growth regulators are already covered by the TP and are also given in the input data for the OP. In practice, transportation crews are sufficiently available and can be hired on demand when necessary. Thus, decisions regarding transportation crews are also excluded from the OP. While the TP works with estimated maturation curves of the sugar cane, the operational planning is intended to work with updated recent values of the sugar cane's maturity, i.e. Pol, reduced sugar and fiber. These values result from the pre-analysis, where cane examples of a certain area are analyzed before the sugar cane is cut. Given the Pol and reduced sugar values (for each field) of the month before the planning as well as the forecasted values for the subsequent month, we estimate the values for each day of the planning by linear interpolation.

After mechanical cutting crews finish their work at the end of each day, they remain at the current field and start working in the beginning of the next day. Manual cutting crews return to a place where they are accommodated. In addition to the previously presented decisions, the OP should suggest the sequence in which each cutting crew cuts the fields. Time and costs to move from one field to another within these cutting sequences must be considered.

4 Mathematical Model

From the modeling view point, both the TP and OP are very similar. This section presents a MIP model for the OP. Regarding the objective and decisions both models have in common, the TP is modeled in a similar manner. The OP uses days as general decision time units and divides each day into a number of time units (denoted by the set I). Clearly, the smaller each time unit, the more precise the planning can be. Throughout our computational experiments, each day is divided into twelve time units, i.e. each time unit represents a period of two hours. The TP uses weeks as decision units only. In addition, decision variables of the TP contain an additional index to distinguish the use of different growth regulators.

For the sake of simplification, the following model does not explicitly state the constraints for vinasse application. The implementation of these constraints is straightforward, guarantying that, at each day, a sufficiently large area is harvested.

4.1 Input Data and Variables

Consider the following input data. D is the ordered set of days that are considered in the operational planning horizon. P is the set of mills. C is the set of cutting crews. F is the set of sugar cane fields and $F_c \subseteq F$ is the set of fields that can be harvested by $c \in C$. I is an ordered set of time instants of all days and $I_d \subseteq I$ denotes the instants at day $d \in D$. The day at instant i is denoted by d_i.

V_p^d is the selling price (in R$) for the ATR from one ton of cane from mill $p \in P$ at $d \in D$. CC_{cf}^d is the cost to cut field $f \in F_c$ by crew $c \in C$ at day $d \in D$. ATR_f^d is a coefficient that represents an increased/decreased sugar level within cane cut from field $f \in F$ at $d \in D$, for example due to previous application of growth regulators. $CT_{cf_1f_2}^d$ is the relocation cost of $c \in C$ from $f_1 \in F_c$ to $f_2 \in F_c$ at $d \in D$. CP_{fp}^d is the cost to process one ton of cane from field $f \in F$ in mill $p \in P$ at day $d \in D$ (may include transportation costs from the field to the mill).

λ_{cf}^{id} denotes the quantity of sugar cane (in tons) cut at day d by crew $c \in C$ at field $f \in F_c$, assuming that c began cutting at instant $i \in I$. $\underline{QC}_c^d$ and $\overline{QC}_c^d$ denote the minimum and maximum cutting capacity limits (in tons) of $c \in C$ at $d \in D$. Fib_f^d denotes the percentage of fiber within sugar cane of $f \in F$ at $d \in D$. The minimum fiber percentages required at a mill $p \in P$ at $d \in D$ is referred to $\underline{Fib}_p^d$. A mill $p \in P$ requires a minimum cane quantity of $\underline{QP}_p^d$ tons and has a maximum capacity of $\overline{QP}_p^d$ tons of cane at $d \in D$.

The mathematical model makes use of the following variables:

$h_{cf}^d \in \{0,1\}$	1, only if $c \in C$ leaves home at $d \in D$ to start its work at $f \in F_c$ at the first available instant of the day.
$k_{cfp} \in \{0,1\}$	1, only if $c \in C$ leaves $p \in P$ and begins its activities at $f \in F_c$.
$n_{c,f}^i \in \{0,1\}$	1, only if $c \in C$ waits one instant at $f \in F_c$ (from i to $i+1$).
$o_{cf_1f_2}^{i_1i_2} \in \{0,1\}$	1, only if $c \in C$ will leave $f_1 \in F_c$ at instant $i_1 \in I$ to arrive at $f_2 \in F_c$ at instant $i_2 \in I$.
$x_{fp} \in \{0,1\}$	1, only if the sugar cane from $f \in F$ will be processed in $p \in P$.
$y_{cf}^{i_1i_2} \in \{0,1\}$	1, only if $c \in C$ starts cutting $f \in F_c$ at instant $i_1 \in I$ and is available again at instant i_2. Index i_2 may be suppressed, as it can be unequivocally computed.
$z_{fp}^d \in \mathbb{R}^+$	quantity of sugar cane (in tons) from $f \in F$ that will be processed in $p \in P$ within $d \in D$.

4.2 Objective Function and Constraints

The objective function maximizes the total profit, composed by the revenue given by the sugar production (depends on selling price and sugar content in cane) and the total cost for cane transportation and processing at the mills as well as harvesting costs and relocation costs for the cutting crews.

$$\max \sum_{d\in D}\sum_{f\in F}\sum_{p\in P}(V_p^d ATR_f^d - CP_{fp}^d)\cdot z_{fp}^d$$
$$- \sum_{i\in I}\sum_{c\in C}\sum_{f\in F} CC_{cf}^{d_i}\cdot y_{cf}^i - \sum_{f_1\in F}\sum_{f_2\in F}\sum_{i\in I}\sum_{c\in C} CT_{cf_1f_2}^{d_i}\cdot o_{cf_1f_2}^i \tag{1}$$

Industrial and Resource Constraints

The industrial and resource related constraints are stated below. Constraints (2) guarantee that all fields are cut during the planning horizon. Constraints (3) define minimum and maximum processing limits for the mills. The minimum percentage of fiber is guaranteed by constraints (4). Constraints (5) define minimum and maximum capacities of the cutting crews. Constraints (6) say that all cut sugar cane must be allocated to a mill. Constraints (7) guarantee that the quantity of processed cane is not higher than the quantity harvested. Let M_f be the maximum productivity of field f throughout all planning days. Then, the set of constraints (8) says that the quantity of cane from a field processed at a certain mill can be non-zero only if the field is allocated to that mill.

$$\sum_{c\in C}\sum_{i\in I} y_{cf}^i = 1 \quad ;\forall f\in F \tag{2}$$

$$\underline{QP}_p^d \le \sum_{f\in F} z_{fp}^d \le \overline{QP}_p^d \quad ;\forall d\in D \;;\forall p\in P \tag{3}$$

$$\sum_{f\in F} Fib_f^d\cdot z_{fp}^d \ge \sum_{f\in F} \underline{Fib}_p^d\cdot z_{fp}^d \quad ;\forall d\in D \;;\forall p\in P \tag{4}$$

$$\underline{QC}_c^d \le \sum_{f\in F}\sum_{i\in I}\lambda_{cf}^{id}\cdot y_{cf}^i \le \overline{QC}_c^d \quad ;\forall d\in D \;;\forall c\in C \tag{5}$$

$$\sum_{c\in C}\sum_{i\in I} y_{cf}^i = \sum_{p\in P} x_{fp} \quad ;\forall f\in F \tag{6}$$

$$\sum_{p\in P} z_{fp}^d \le \sum_{c\in C}\sum_{i\in I}\lambda_{cf}^{id}\cdot y_{cf}^i \quad ;\forall d\in D \;;\forall f\in F \tag{7}$$

$$\sum_{d\in D} z_{fp}^d \le M_f\cdot x_{fp} \quad ;\forall f\in F \;;\forall p\in P \tag{8}$$

Cutting Crews Network Flow Constraints

The cutting and relocation activities of each cutting crew are handled by a binary flow through time and the fields that the crew may cut. Each day is split into a number of time instants, at which an activity may finish and another activity may start. Each crew possesses its own network that is independent of the ones of other crews. Each crew activity (harvesting, relocation and waiting) is represented by an arc that leaves a field/instant-node and enters another field/instant-node: cutting arcs enter at the same field at a later time instant, waiting arcs enter at the next available time instant and relocation arcs enter at another field at some later time instant (see Figure 2). The length of an arc represents the time consumed by the activity and is based on the cutting rate, relocation speed and daily time availability of the crew. In that way, a cutting crew may relocate from one field to another and cut several fields at the same day. Also, cutting at the same field may take more than one day.

Flow initialization - initial crew positions. Let $l_c \in F \cup P$ denote the location (either a field or a mill), where cutting crew $c \in C$ is located in the beginning of the planning. Let $C_p \subseteq C$ be the set of crews that are initially located at a mill and p_c (with $c \in C_p$) denote the mill at which c is located. The initial position of the crews determines how the binary flow is inserted into the network:

$$\sum_{f \in F} k_{cfp_c} = 1 \quad ;\forall c \in C_p \tag{9}$$

$$y_{cf}^{i_c^0} + n_{cf}^{i_c^0} + \sum_{f_2 \in F} o_{cff_2}^{i_c^0} = \begin{cases} 1, \ if \ f = l_c \ \wedge \ c \notin C_p \\ k_{cfp_c}, \ if \ c \in C_p \\ 0, \ otherwise. \end{cases} \quad ;\forall c \in C \ ;\forall f \in F \tag{10}$$

Constraints (9) relocate all cutting crews located at a mill to one of their eligible fields. Then, constraints (10) insert a binary flow (RHS) into the node of the first available instant i_c^0 at the field the crew is located. Such flow is then available to cut a field, wait at the field or relocate to another one (LHS).

Flow conservation - cutting, waiting and relocation. Once the flow entered the network, it must pass along time. The flow that enters a node at instant i must also leave it. Flow can enter from cutting variables for the field, from a waiting variable at the previous instant or by relocating from one of the other fields. If flow enters the node, it leaves it again by cutting the field, waiting one instant or moving to another eligible field. Flow conservation must distinguish mechanical and manual cutting crews. Mechanical cutting crews remain on the field during the night, whereas manual crews return to their accommodation. Let I_c contain all instants except the first available instant of each day if c is a manual cutting crew. Otherwise, let I_c contain all instants except the very first instant of the planning:

$$\sum_{i' \in I} y_{cf}^{i'i} + n_{cf}^{i-1} + \sum_{f' \in F} \sum_{i' \in I} o_{cf'f}^{i'i} = y_{cf}^{i} + n_{cf}^{i} + \sum_{f' \in F} o_{cff'}^{i} \quad ;\forall i \in I_c \ ;\forall c \in C \ ;\forall f \in F \tag{11}$$

Figure 2 exemplifies a network flow for mechanical and manual cutting crews. The nodes in the gray area are not available for work. Hence, all flow variables skip the nodes of unavailable instants. Manual cutting crews move to their accommodation at the end of the day and return to any eligible field on the next day. Arcs for cutting and waiting that would enter into the first available instant of a day now enter the accommodation node. From there, flow passes back to the fields. For manual cutting crews, the previous equation is valid for the first available instant of each day. The flow that would have entered in the first node of each day now enters into the accommodation node. This is guaranteed by the following equation, where I_c represents a set with the first available instants of all days of the cutting crew c. Note that this constraint is not generated for the node of the very first available instant of the entire planning:

$$\sum_{f \in F} \sum_{i' \in I} (y_{cf}^{i'i} + n_{c,f}^{i-1} + \sum_{f' \in F} \sum_{i' \in I} o_{cf'f}^{i'i}) = \sum_{f \in F} h_{cf}^{d_i} \ ;\forall i \in I_c^{\setminus \{i_0\}} \ ;\forall c \in C \tag{12}$$

Finally, the following equation distributes the flow from the accommodation node to all plantation fields for each cutting crew:

$$h_{cf}^{d_i} = y_{cf}^{i} + n_{cf}^{i} + \sum_{f' \in F} o_{cff'}^{i} \ ;\forall i \in I_c^{\setminus \{i_0\}} \ ;\forall c \in C \ ;\forall f \in F \tag{13}$$

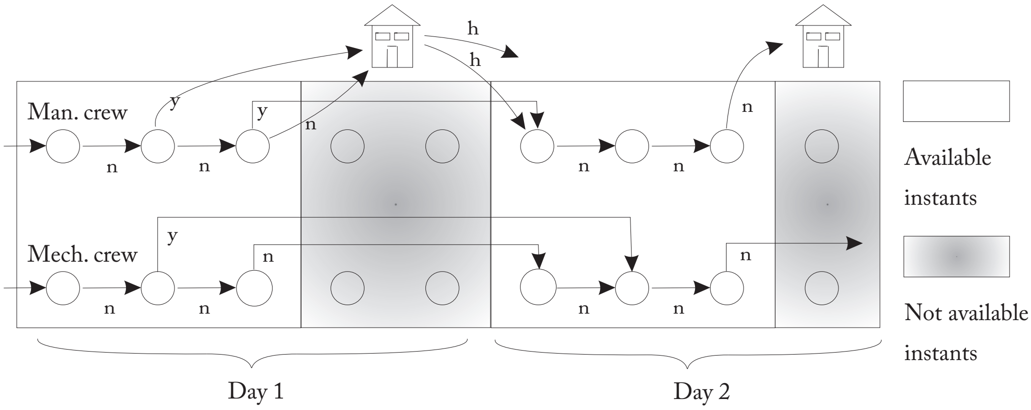

Figure 2: Example networks for cutting crews

5 Valid Inequalities

The linear relaxation of this problem turned out to be strongly fractional. Figure 3 (a) illustrates the route of a mechanical cutting crew in the optimal solution of the linear relaxation for an instance provided by our industrial partner. The total flow from the initial location at the mill is divided into several fields which are then repeatedly cut until the end of the planning. Manual cutting crews behave similar, returning to their accommodation at the end of a day and returning to the same field at the next day. In this section, we introduce three types of valid inequalities (VI) to strengthen the MIP formulation.

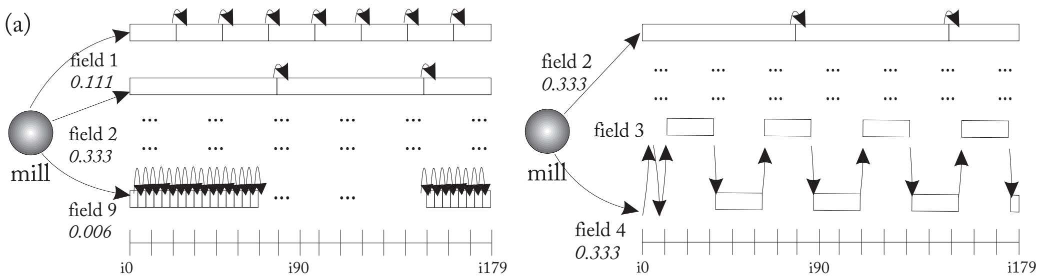

Figure 3: Route of a mechanical cutting crew in the optimal solution of the linear relaxation without inequalities (a) and with inequality type 1 (b)

5.1 VI 1: Relocations throughout entire planning

The analysis of the optimal solutions of the linear relaxations exposed that the linear relaxation's solution prefers not investing in relocation, as this is consuming in time and costs. However, in an integer solution, relocation from one field to another is required to cut both of them. In addition to the common relocation, manual cutting crews may relocate by using h variables leaving from their accommodation to a field. Consider a cutting crew that cuts n fields throughout the entire planning period. This crew must perform at least $n-1$ relocations in order to visit all fields (for mechanical crews, exclude the h variables):

$$\sum_{f_1\in F}\sum_{f_2\in F}\sum_{i\in I} o^i_{cf_1f_2} + \sum_{f\in F}\sum_{d\in D} h^d_{cf} \geq \sum_{f\in F}\sum_{i\in I} y^i_{cf} - 1 \;\; ;\forall c \in C$$

5.2 VI 2: Relocations at each field

Inequality 1 forces the LP solution to perform relocations with an equivalent flow value in order to compensate the cuts of a preferred field f^*. These additional relocations are performed without interfering the continuous harvesting of f^*. Figure 3 (b) exemplifies this situation. The cutting crew prefers to repeatedly harvest field 2 (in this case three times). At the same time, a number of relocations of equivalent flow are performed in order to compensate the repeated cuts. Such a behavior can be avoided by adding constraints that force relocation at each field. The flow entering in a field and the flow leaving from a field are considered separately.

In flow. A cutting crew should only invest a certain flow quantity in harvesting a field, if this flow quantity (or more) has been inserted into that field by relocation before (for mechanical crews, there will be no h variables):

$$\sum_{p\in P} k_{cf_1p} + \sum_{f_2\in F}\sum_{i\in I} o^i_{cf_2f_1} + \sum_{d\in D} h^d_{cf_1} + \Phi_{cf_1} \geq \sum_{i\in I} y^i_{cf_1} \;\; ;\forall c \in C \;\; ;\forall f_1 \in F$$

If the cutting crew is initially located at a field, the k variables are not used in this VI. Furthermore, if c is initially located at field f, then $\Phi_{cf} = 1$, otherwise $\Phi_{cf} = 0$.

Out flow. All flow used to harvest a field must also leave this field by making use of relocation variables. At the end of the planning, the flow may leave the network without relocation (subtracted on RHS). Let i^0_d be the first instant at day d. At each field holds:

$$\sum_{f_2\in F}\sum_{i\in I} o^i_{cf_1f_2} + \geq \sum_{i_1\in I} y^{i_1}_{cf_1} - 1; \;\; ;\forall c \in C \;\; ;\forall f_1 \in F$$

5.3 VI 3: Relocations at each field at each day

In flow. We may strengthen the previous inequalities by stating them for each day separately. At the first day, the input flow may come from a mill or from the cutting crew if it is initially located at that field. Again, if c is initially located at field f, then $\Phi_{c,f} = 1$, otherwise $\Phi_{c,f} = 0$.

$$\sum_{p\in P} k_{cf_1p} + \sum_{f_2\in F}\sum_{i_1\in I}\sum_{i_2\in I_{d_0}} o^{i_1i_2}_{cf_2f_1} + \Phi_{cf_1} \geq \sum_{i\in I_{d_0}} y^i_{cf_1}; \;\; ;\forall c \in C \;\; ;\forall f_1 \in F$$

During all days except the first one, flow will not come from a mill. Instead, it may come from a waiting variable n that leaves from the last instant of the previous day and enters at the first instant of the current day. Let i^*_d be the last instant at day d. For each day holds (for mechanical crews, the h variables will not be considered):

$$\sum_{f_2\in F}\sum_{i_1\in I_d} o^{i_1}_{cf_2f_1} + n^{i^*_{d-1}}_{cf_1} + h^d_{cf} \geq \sum_{i_1\in I_d} y^{i_1}_{cf_1}; \;\; ;\forall d \in D \;\; ;\forall c \in C \;\; ;\forall f_1 \in F$$

Out flow. The out flow inequalities for mechanical cutting crews consider all outgoing relocation variables at a certain day as well as the waiting variables that leave from the last available instant of that day. The total flow accumulated by these variables must be greater or equal than all flow invested in field cuts terminating at the current day. Let i'_d be the first instant and i^*_d be the last instant at day d. These inequalities can be formulated as:

$$\sum_{f_2\in F}\sum_{i_1\in I_d} o^{i_1}_{cf_1f_2} + \geq \sum_{i_1\in I}\sum_{i_2\in I_d} y^{i_1i_2}_{cf_1} \;\; ;\forall d \in D \;\; ;\forall c \in C \;\; ;\forall f_1 \in F$$

Note that the out flow inequalities above are illustrated only for mechanical crews. They can be easily adapted to the manual crews. However, computational experiments showed that they did not show much effect in the upper bound improvement when applied to manual crews, since many cutting variables appear on both sides of the inequality.

6 Solution Techniques and Results

This section deals with the solution techniques and computational experiments that have been performed. As it will be shown further below, the TP can be easily solved by the commercial MIP solver. However, the OP is much more difficult to solve. In the following, we will discuss the instances that have been provided for both planning, basic computational experiments and a series of solution techniques to facilitate the solution of the OP. These techniques include pre-processing of the input data, the construction of hot-start solutions, the evaluation of the valid inequalities to strengthen the formulation and a specialized algorithm to solve the problem.

Instances. The sugar producer provided instances for the tactical and operational planning. For the TP, 14 such real-world (RW) instances were provided containing up to 1155 plantation fields, using one aggregated transportation crew. Based on these instances, further nine instances have been generated by increasing the mills' processing demands or decreasing the cutting crews' capacities. For the OP, four RW instance sets with a total of 25 instances were provided. The sets correspond to different moments in the harvest season and contain between 19 and 334 plantation fields, one or two sugar cane mills, between five and 21 cutting crews and a planning horizon of up to 16 days. Additionally, 15 artificial instances were designed that provide a broad variety of characteristics. The instances were divided into groups, each with a different number of plantation fields: four instances with 20 fields, five instances with 50 fields and six instances with 100 fields. The planning horizon varies from 15 to 30 days. Each configuration is available with different values for the mill's minimum processing demands. All OP instances can be found at: `http://w1.cirrelt.ca/~jena/instances.htm`.

Computational Experiments. Computational experiments were carried out on a Personal Computer with an Intel(R) Core(TM)2 Duo 2.33 GHz CPU and 2 GByte memory. The C++ implementation was compiled with Visual Studio 2008, using Microsoft Windows Vista 32bit. All experiments presented throughout this work involve the branching and polishing phases of IBM ILOG CPLEX 11.2. The Brazilian sugar producer involved in the design process of the model required a limit of 30 minutes execution time to solve each tactical and operational planning problem. Hence, the branching and polishing phases were limited to 15 minutes each.

For all TP instances, using the original input data on the previously presented model, CPLEX closed the optimality gap to at least 0.5% within less than ten minutes within the branching phase. The solution of the OP has been been found to be significantly more difficult. On the original input data, CPLEX has often not been able to find feasible solutions in the given time limit. For many other instances, the optimality gap has not been closed very well. This suggested further effort in order to facilitate the problems' solution. It follows.

6.1 Preprocessing

As the computational experiments showed, CPLEX presented problems in solving OP instances of realistic size. Certain pre-processing techniques have been applied in order to decrease the problem size while the optimal solutions of the problems are only marginally affected or not at all.

Node/variable pruning and Field grouping. Variables are pruned if they represent decisions that are not feasible in practice. A non-terminal node with degree 2 reduction is performed. In addition, fields with the same characteristics were grouped to field blocks within the instances provided by the sugar producer. This significantly reduced the number of nodes within the graph of fields.

Distance filtering. Reducing the routing possibilities between fields for cutting crews also turned out to be very effective to facilitate the solution process. Clearly, the more routes between fields are available (i.e., the more dense the graph of fields), the more options the crews have to relocate from one field to another and the better may be the optimal solution to the problem. However, the more distances are included, the larger the problem. Experiments showed that the following filtering strategy significantly facilitates the solution of the OP: a minimal spanning tree guarantees connectivity of the distance graph. Then, we add outgoing arcs to each node such that the number of outgoing distances is fairly balanced for all nodes.

6.2 Hot Start with Heuristic Solutions

Heuristic methods are used to provide starting solutions for the MIP solver. The heuristic implemented in this work constructs a harvesting sequence of plantation fields for each cutting crew. The planning is performed sequentially, for one crew after another. Each planning consists of a sequence of fields. For each field, the heuristic determines the time instant at which the field shall be harvested (y variables) and the mill where its cane shall be processed (x variables). At each step, the heuristic greedily selects the field f_n which has the best relation between the quantity of sugar cane cut at the field and the time spent to relocate to the field as well as to cut it. Once the fields are selected, the method distributes the field cuts along the total planning period to improve the mills' processing demands which tend to have a uniform distribution along the planning. Finally, a mill is selected to process the sugar cane of each of the harvested fields. For each field, a mill is selected such that the total violation of the minimum processing demands at the sugar cane mills is minimized.

The heuristic was evaluated by means of the following experiment. Consider a set of 48 initial solutions, created through the following strategy: six different cutting crew sequences were considered. In one sequence, the cutting crews are sorted in increasing order of the number of the fields that they can cut. The other five cutting crew sequences are randomly determined. For each of these sequences, two constructions based on the field selection without randomization and six with randomization are performed. Half of these constructions contain the harvesting distribution along the planning time, whereas the other half does not. Considering the best of these 48 solutions for each instance, its average optimality gap (from the UB obtained by the linear relaxation) over all instances is 28.71%.

Table 2 compares the average optimality gaps (compared to linear relaxation bound) after the optimization over all RW and the artificial instances (grouped by instance set) with and without providing the set of starting solutions to the MIP solver. The solver

Instance set	Without initial solutions		With initial solutions
	# no sols	gap %	gap %
Avg Art20	-	2.84	10.72
Avg Art50	-	36.06	2.68
Avg Art100	-	130.57	3.06
Avg RW	4	6.13	4.07

Table 2: Impact of starting solutions on final solution quality

	LR	Avg Artificial			Avg Real-World		
Used ineq.	(sec)	gap %	gap* %	UBI %	gap %	gap* %	UBI %
Without ineq.	67	9.86	4.97	-	10.11	3.36	-
Inequality 1	125	3.83	3.16	4.08	5.54	3.25	29.07
Inequality 2	105	6.93	6.63	4.76	4.16	3.79	32.22
Inequality 3	218	5.31	5.00	4.54	5.49	3.87	31.44
Ineq. 1+2+3	208	4.50	4.46	4.35	8.89	8.43	33.80

Table 3: Impact of the valid inequalities on final solution quality

itself could not find feasible solutions at four instances within the given time limit. In addition, the quality of the final solutions significantly improved as the solver did not spend time in the initial search for feasible solutions.

6.3 Impact of the Valid Inequalities

Experiments have been performed in order to compare the impact of the inequalities to the obtained upper bounds and the optimization process. The experiments include the previously introduced pre-processing techniques as well as the set of starting solutions. Table 3 reports the average time to solve the linear relaxation (*LR*), the relative improvement of the first upper bound found (the value of the linear relaxation's solution) using the inequalities (*UBI* %), the average deviation from optimum reported by CPLEX at the end of the optimization (*gap* %) and the average deviation from the best upper bound known for the instance (*gap** %). Instances for which no solution have been found were not considered in the average values.

In all experiments, the additional inequalities resulted in an increased solution time for the linear relaxation. However, their use has shown to be very effective to improve the quality of the final integer solutions, in particular for the RW instances. The linear relaxation bound improved by at least 20% for all inequality types. The use of all inequality types led to a bound improvement of more than 33% for the RW instances. The results suggest the use of *Inequality 1* within the mathematical model for time limited executions, as its use results in a significantly improved average solution quality.

6.4 Problem Splitting and Assembling

Many problems can be decomposed into subproblems, connected only by a few linking constraints. Mathematical decomposition or matheuristics that solve the subproblems separately are promising approaches when the original problem is large and contains only a few of such linking constraints. We focus on the latter approach by considering the harvest sequence of each cutting crew separately. The problem is divided into one subproblem for each crew, sharing only the fields and mills as common resources. This approach is interesting in particular for instances where crews have mostly disjoint field sets.

Algorithm. The cutting crews' planning is performed one after another following a certain order within the list of cutting crews. For each subproblem, the MIP is created and solved. The variables keeping track of the fields harvesting state as well as the mill capacities for the global solution are updated. The solutions for all subproblems are then aggregated to one global solution for the original problem. Finally, the complete problem is considered to further improve the solution for the original problem. The sequence in which the crews' planning are performed clearly influences the final solution. An increasing and decreasing ordering in respect of the number of fields that are eligible for the cutting crew (i.e., $|F_c|$) is considered.

The performed experiments for this algorithm use the set of starting solutions and include the valid inequalities of type 1 and distance filtering. The first 25 minutes were uniformly divided into smaller optimization periods, one for each cutting crew. The remaining five minutes were used to improve the overall problem. The subproblems for each cutting crew spent $\frac{2}{3}$ of the time in branching and the remaining $\frac{1}{3}$ of the time in polishing.

Instances	Normal	No Ineq. Segr, Incr	No Ineq. Segr, Decr	Ineq. 1 Segr, Incr	Ineq. 1 Segr, Decr
Art20	10.72	16.83	2.88	2.90	14.40
Art50	2.68	6.05	3.90	6.07	3.77
Art100	3.06	3.43	2.56	3.66	2.70
RW100	2.35	1.56	1.48	1.74	1.68
RW102	9.75	4.61	25.93	4.62	25.26
RW103	2.25	0.95	1.07	0.67	0.70
RW106	0.76	0.52	0.51	0.54	0.43
Artificial	4.97	7.88	3.09	4.26	6.17
RW	3.36	1.71	5.98	1.68	5.77
All	3.96	4.02	4.90	2.65	5.92

Table 4: Comparison of optimality gaps for different solution strategies

Table 4 shows the average optimality gaps (in % from the best known solutions) for all instance sets for different solution strategies: the direct solution of the original problem (*Normal*, without use of inequalities) and four combinations for the problem splitting strategy with/without inequalities, considering increasing/decreasing order for the sequence of crews. Some of the configurations of this approach remarkably improved the results of the traditional solution approach. The increasing ordering of the cutting crews tends to perform better on the RW instances. The decreasing order demonstrated better results on the artificial instances. A very strong solution quality difference is perceived for instance set RW102. Table 5 focuses on these instances and compares configurations with increasing and decreasing ordering sequences with and without inequalities. All instances contain two cutting crews with a low occupation rate and three cutting crews with a high occupation rate. Although the average number of not harvested fields (# *nh*) is almost the same in all approaches, the total sum of cut sugar cane is much higher within the solutions of the configuration with the increasing crew ordering. This behavior, observed throughout all instances of this set, is likely to confirm the assumption made for a decreasing ordering: the planning for the two crews with few fields are performed as the last ones. An analysis showed that, as the field intersection is very high, the firstly planned crews (where $|F_c|$ is large) selected fields that can also be cut by the two crews for which $|F_c|$ is small. Hence, the two crews with small field sets $|F_c|$ had less alternatives to harvest fields and resulted in more spare time. On the other hand, by using an increasing order of $|F_c|$, the planning of the two crews with small $|F_c|$ will be performed in before and have thus the possibility to harvest all fields within their field sets. Subsequent crews then harvest other fields. Crews with small field sets are thus able to cut more, while the other crews harvest the same quantity as in the approach using a decreasing order. This behavior suggests that an increasing order is selected when the field set $|F_c|$ are not mostly disjoint.

Solution strategy	Avg gap %	# nh	Total harvest (tons)
No Cuts. Incr	4.61	60.20	80820.69
No Cuts. Decr	25.93	59.60	74571.41
Inequality 1. Incr	4.62	60.20	80799.32
Inequality 1. Decr	25.26	60.60	74758.42

Table 5: Impact of increasing/decreasing crew order in split/assemble (instance set RW102)

7 Case Study for the Operational Planning

We illustrate the operational planning at one of the industrial instances from instance set RW106. The instance represents 15 days extracted from a solution for a tactical planning of our industrial partner. It holds 43 harvesting regions which have already been assigned to a single mill located in the state of São Paulo. Harvesting resources include three mechanical harvesting crews and two manual crews. The manual crews work 8hs per day and harvest 66 tons/h in average. Mechanical crews work 16hs per day. One of them harvests 112 tons/h in average and the other two harvest 89 tons/h in average. The mill aims at crushing a minimum of 4500 tons of sugar cane per day, which is tight when compared with the capacities of the harvesting resources.

The manual planning from the industrial partner was not available to compare with our solutions. We thus compared with the best of the heuristically generated solutions as explained in Section 6.2. In practice, harvesting planners commonly prefer to harvest fields which are close to each other instead of relocating the crews over longer distances. Latter one may be beneficial to harvest fields close to its maturation peak. However, taking this into consideration in a manual planning is very difficult. We may thus assume that the quality of our heuristic solutions are representative for a planning in practice. Note that, if we want to avoid the relocation of crews over long distances in our mathematical model, we may simply apply a distance filtering with a maximum distance.

The selected heuristic planning is the best of the generated hot-start solutions. The optimized planning is based on a CPLEX solution with proven optimality gap smaller than 1%. For the heuristic planning, each day was discretized into 24 time instants. For the optimized planning, the problem was discretized into 12 time instants per day (as the problem got too large when a discretization into more than 12 instants has been used).

Tables 6 and 7 resume the quantities of sugar cane harvested according to the heuristic and optimized planning, respectively. $C1$ and $C2$ are manual crews, $C3$, $C4$ and $C5$ are mechanical crews. Even though we discretized each day in the optimized planning in less time instants (and thus harvesting and relocation blocks tend reserve more time as they are rounded up to the next highest time instant), the optimized planning harvests slightly more sugar cane than the heuristic planning (about 0.5%). In addition, in the optimized planning, the total quantity of daily harvested cane is better distributed than in the heuristic planning. Latter one violates the minimum demand of 4500 tons at more than half of the days, while the optimized planning satisfies this demand at all days.

The tables also indicate the average Pol percentage in the cane at the moment it is harvested (*Avg Pol*). While the heuristic planning harvests fields at an average Pol of 14.80%, the optimized planning increases the average to 15.13%. This reflects an increase of 2.7% of the total processed Pol quantity and finally an increase in the estimated profit of 2.6% for this operational planning. It is thus very likely that a combined use of the

Day	Tons harvested by crew C1	C2	C3	C4	C5	Total	Avg Pol (%)
1	445.5	440.1	1,794.0	366.4	1,363.5	4,409.5	14.7
2	454.4	528.0	1,794.0	1,302.6	1,426.0	5,505.0	14.78
3	438.3	528.0	1,794.0	496.0	1,426.0	4,682.3	14.82
4	406.4	528.0	1,712.4	1,391.3	1,426.0	5,464.0	14.89
5	456.6	446.4	1,794.0	372.0	1,311.1	4,380.1	14.78
6	262.2	528.0	1,794.0	406.6	1,346.3	4,337.0	14.91
7	381.0	397.4	1,680.3	420.4	1,426.0	4,305.0	15.31
8	528.0	528.0	1,794.0	1,217.1	1,305.7	5,372.8	15.03
9	528.0	528.0	1,687.7	558.0	1,363.4	4,665.0	14.71
10	528.0	528.0	1,794.0	759.8	1,356.0	4,965.8	14.75
11	528.0	438.6	1,674.7	513.0	1,303.9	4,458.3	14.87
12	528.0	528.0	1,794.0	115.4	1,319.5	4,284.8	15.04
13	528.0	528.0	1,669.8	144.5	1,322.9	4,193.2	14.35
14	528.0	469.5	1,678.3	267.7	1,426.0	4,369.6	14.54
15	376.2	465.5	1,794.0	177.2	309.8	3,122.6	14.49
All	6,916.4	7,409.5	26,249.2	8,507.8	19,431.9	68,514.9	14.80

Table 6: Quantity and average Pol of cane harvested in the heuristic planning

Day	Tons harvested by crew C1	C2	C3	C4	C5	Total	Avg Pol (%)
1	528.0	526.3	1,794.0	769.8	1,037.1	4,655.1	14.93
2	528.0	500.6	1,674.7	1,161.2	640.2	4,504.6	14.85
3	528.0	528.0	652.4	1,426.0	1,426.0	4,560.4	14.90
4	528.0	528.0	1,794.0	487.4	1,278.8	4,616.2	14.71
5	528.0	381.5	739.0	1,426.0	1,426.0	4,500.5	14.59
6	528.0	465.5	1,398.0	738.3	1,426.0	4,555.8	14.98
7	528.0	528.0	1,794.0	1,188.2	516.4	4,554.6	14.70
8	376.2	528.0	1,393.3	927.7	1,281.9	4,507.1	14.69
9	306.2	528.0	1,794.0	1,223.7	658.9	4,510.8	15.15
10	406.4	402.4	1,794.0	479.8	1,426.0	4,508.6	15.22
11	440.0	528.0	1,794.0	1,426.0	347.5	4,535.5	15.63
12	528.0	309.4	1,159.3	1,426.0	1,136.9	4,559.5	15.45
13	528.0	420.0	1,794.0	1,116.7	907.5	4,766.1	15.61
14	502.6	381.0	1,794.0	1,179.9	1,133.5	4,991.0	15.59
15	454.4	421.1	801.3	1,403.1	1,426.0	4,505.8	15.88
All	7,237.7	6,975.7	22,169.9	16,379.6	16,068.6	68,831.7	15.13

Table 7: Quantity and average Pol of cane harvested in the optimized planning

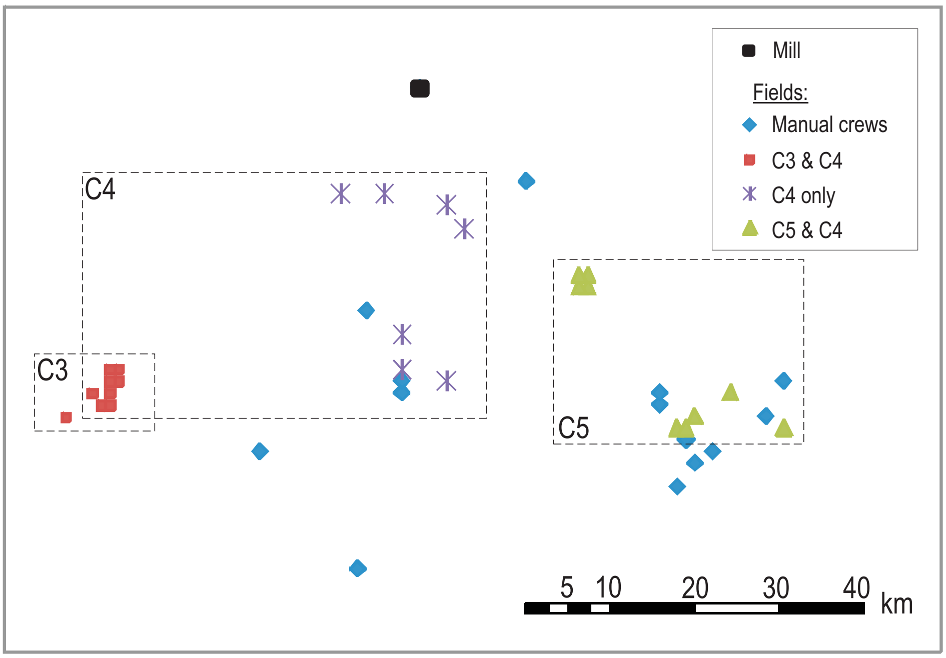

Figure 4: Mill and harvest regions for an operational planning

tactical and operational planning results in a harvest planning that maximizes the total sugar outcome much more efficient than traditional planning methods.

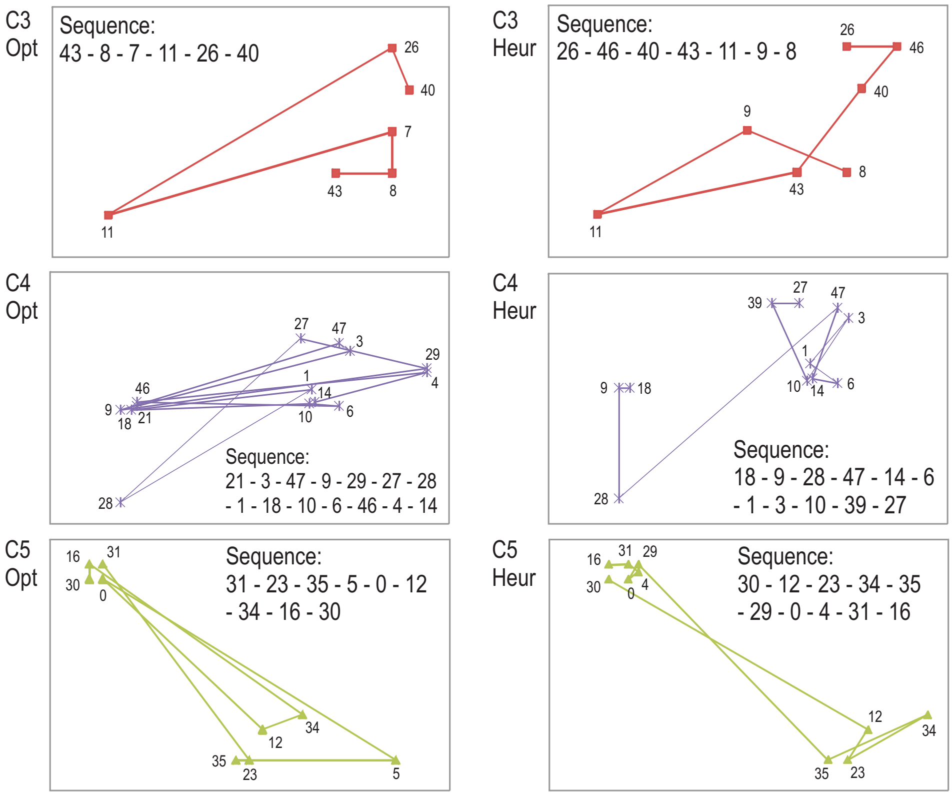

Figure 5: Optimized and heuristic harvest sequences for the mechanical crews

Figure 4 illustrates the harvest regions and the mill for the studied instance. Each harvest region is indicated by a symbol that stands for the cutting crew(s) which may harvest the field. The sets of fields for the manual and mechanical crews are disjoint. For the mechanical crews, the field sets for C3 and C5 are disjoint. C4 may harvest all fields. The set of fields harvested by each of the mechanical crews are framed by a dashed rectangle (labeled *C*3, *C*4 and *C*5 to indicate the corresponding crew). Figure 5 draws the fields for each of the crews to a larger scale. For each crew, its harvesting sequences according to the optimized and heuristic planning are illustrated. Note that these sequences do not necessarily include the same set of fields. For crews C4 and C5 one can clearly see that the crews relocate over significantly larger distances in the optimized planning when compared to the heuristic planning. The increased crew relocation is motivated by the attempt to harvest fields close to their maturation peak. For crew C3, the difference in the relocation distance is less visible, since its harvested fields are very close one to another.

In the heuristic planning, the average relocation distance between two harvest regions for the crews C3, C4 and C5 are 2.44km, 15.93km and 7.17km, respectively. In the optimized planning, the average relocation distances increase to 2.73km, 32.11km and 12.79km, respectively. The total distance relocated by the three crews throughout the entire planning amounts to 238.47km in the heuristic planning and 533.45km in the optimized planning. Even though the total distance almost doubled, this amount is still very small when compared to the other relocation activities such as the cane transportation itself (from the fields to the mill). The additional costs and increased emissions linked to the larger relocation distances of the cutting crews are thus very small.

8 Conclusions

An approach for the tactical and the operational planning of an important agricultural activity has been presented. The principal concern in both planning is to harvest the fields close to their maturation peaks, i.e., when the sugar content is highest. The evaluation of a near-optimal solution for an industrial instance showed that the proposed planning holds a significant potential to increase the total profit. By harvesting fields close to their maturation peaks, cutting crews increase their relocation distances. However, in the studied context, the total profit increased by 2.6%.

As most of the medium and long term planning problems, the tactical planning is well handled by current commercial MIP solver within the (short) computation time required. For the operational planning, the problem gets significantly more difficult to solve. The time limit of thirty minutes demanded the application of techniques currently in use in most Operations Research centers. A deeper study of the proposed formulation resulted in the proposal of valid inequalities to strengthen it. Preprocessing and tailored reduction of the instances information were applied to reduce the model size. Hot start solutions were provided to make better use of the MIP solver within the allowed computation time. Finally, the matheuristic technique of splitting and assembling the problem helped the MIP solver finding feasible integer solution. With all this, the proposed method was capable to consistently find feasible solutions with integrality gaps below 5%. Mathematical decomposition such as Lagrangean Relaxation or Benders Decomposition may be promising directions for future research.

Provided that almost all application oriented research are restricted to a single research group, we try to change this by making all the instances used available on the web.

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