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Programming and scheduling sugarcane harvesting fronts: model and solution methods for large-scale problems

Programação e sequenciamento das frentes de colheita de cana-de-açúcar: modelo e métodos de solução para problemas de grande porte

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Abstract: In a recent study, optimization models were proposed for programming and scheduling sugarcane harvesting fronts. This is a complex agricultural and logistic problem comprising various factors, such as raw material maturation stage, harvesting at the agricultural unit, transporting of raw material to the plant, and milling capacities of the plant. In this study, one of the optimization models previously studied was used to represent this problem using Mixed Integer Programming (MIP) of a lot sizing and scheduling model in parallel machines with sequence dependent setup times and costs. The proposed methods are based on MIP heuristics to solve this model in a real situation of a harvest season of a typical company from this sector inspired by harvest block aggregation heuristics, relax-and-fix constructive heuristics, and fix-and-optimize improvement heuristics. To compare the performance of the heuristic methods, various experiments were conducted using different combinations and variations of these methods. Three approaches were able to produce good quality solutions. One of them is described in detail and analyzed in this study, showing promising results in terms of making programming and scheduling decisions concerning sugarcane harvesting fronts.

Keywords: Sugarcane harvest programming; Production lot sizing and scheduling; Mixed integer programming; Relax-and-fix and fix-and-optimize heuristics.

Resumo: *Em um estudo anterior recente, modelos de otimização para a programação e o sequenciamento das frentes de colheita de cana-de-açúcar foram propostos. Esse é um problema agrícola e logístico complexo que envolve vários fatores, tais como o estágio de maturação da matéria-prima, a colheita na unidade agrícola e o transporte dessa matéria-prima para a unidade industrial, bem como a capacidade de moagem da unidade industrial. No presente estudo, aplica-se um dos modelos de otimização do estudo anterior para representar esse problema por meio de um modelo de programação inteira mista (PIM) de dimensionamento e sequenciamento de lotes da produção em máquinas paralelas com custos e tempos de setup dependentes da sequência. Propõem-se métodos baseados em heurísticas PIM para resolver esse modelo em uma situação real de uma safra de uma empresa típica do setor, inspirados em uma heurística de agregação de blocos de colheita, em heurísticas de construção do tipo relax-and-fix e heurísticas de melhoria do tipo fix-and-optimize. Para comparar os desempenhos desses métodos heurísticos foram realizados vários experimentos com diferentes combinações e variações desses métodos, e três abordagens foram capazes de gerar soluções de boa qualidade, sendo que uma delas é aqui detalhada e analisada, com resultados promissores para apoiar decisões de programação e sequenciamento das frentes de colheita de cana-de-açúcar.*

Palavras-chave: *Programação de colheita de cana-de-açúcar; Dimensionamento e sequenciamento de lotes de produção; Programação inteira mista; Heurísticas relax-and-fix e fix-and-optimize.*

1 Introduction

Operational research approaches applied to programming production and logistics in agro- industry have been widely studied in the literature (Ahumada & Villalobos, 2009; Junqueira & Morabito, 2012; Plà et al., 2014; Plà-Aragones, 2015). In this context, sugarcane crop harvest programming is a complex problem that involves various factors such as the raw material maturation stage, harvesting

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at the agricultural unit, transporting raw material to the plant, as well as the milling capacities of the plant. The latter is a critical factor for integrating the agricultural and industrial processes. According to Junqueira & Morabito (2017), part of this complexity is due to dividing the agricultural operation into various harvesting fronts, as well as the difficulties of programming and scheduling these fronts over time in order to maintain an average transport capacity of sugarcane for the plant, as the fronts change harvest blocks. Maintaining this average transport capacity could become unfeasible if all the harvesting effort were concentrated only in some points (for example, all fronts are located in only one harvest block) because either resources could be in excess (if most of these fronts are located too near the plant) or there could be a lack if the fronts were too far away.

Various studies have addressed planning sugarcane harvesting, such as: Higgins et al. (1998, 2004a, b), Higgins (1999, 2002) and Higgins & Muchow (2003) in the Australian context; Grunow et al. (2007) in the Venezuelan context and Jena & Poggi (2013) in the Brazilian context. However, these studies either disregard the division into harvesting fronts or predefine it by harvest blocks. In a previous study, Junqueira & Morabito (2017) were inspired by the General Lotsizing and Scheduling Problem for Parallel Production Lines (GLSPPL) proposed by Meyr (2002) and Meyr & Mann (2013), which presents three models concerned with planning sugarcane harvesting considering harvesting fronts. According to the analogy used by the authors, the harvest blocks are represented by the GLSPPL lots, whereas the harvesting fronts are represented by the production lines.

In contrast with other studies that predominantly use sucrose content estimates to assess the ripeness of the sugarcane planted which indicates the optimal harvesting period for an area, Junqueira & Morabito (2017) considered the Length of Time of Industrial Use (LTIU) for each harvesting block to determine the time-window at which a given area could be best harvested. Although they are interesting indicators for the expected income of the raw material, the sucrose content estimates may not be repeated in the next harvest due to: climate variations, soil fertilization, pest problems, diseases, as well as other biological factors that could affect the plant's behavior. In contrast, the LTIU results from a comprehensive agronomic evaluation carried out by the plant´s technical team, as well as from other institutions that develop sugarcane varieties. In addition to the ripeness, the LTIU is formed considering other characteristics of the planted variety, such as if it easy to sprout, tendency to flower, ripening response and irrigation.

The models presented in Junqueira & Morabito (2017) also take into account the harvest potential and the transport variable per harvest block. Characteristics such as the expected productivity of the crop (tons per ha), the planting distance and number of maneuvers vary, depending on the area, and directly affect the hourly production rate of harvesting machines. Similarly, the distance between the harvesting area and the plant, as well as the vehicles' speed have an impact on the transportation rate of the trucks. Trying to find a balance between the harvesting and transportation capacities is essential to reduce costs caused by idle resources which, according to the authors, are significant. However, a reduction in resources should not lead to a failure in supplying raw material to the industry, nor a harvest that is out of season from that predicted by the LTIU as these marginal costs could be significantly higher than those of idleness. The other models reported in the literature take into account only the distance as a dependent variable of the harvest area, which should be balanced throughout the whole harvest season.

Despite the fact that this approach seems promising, Junqueira & Morabito (2017) solved the problem only for small samples, with few hundreds of constraints and variables, and dozens of these discrete variables. In order to address the actual sugarcane harvesting planning, Higgins et al. (2004b), Higgins & Laredo (2006), as well as Jena & Poggi (2013) proposed methods that aggregate harvest blocks in order to reduce the number of variables involved. In parallel, heuristic methods based on MIP, such as *relax-and-fix*, presented by Pochet & Wolsey (2006) and *fix-and-optimize*, proposed by Helber & Sahling (2010), have been widely used to solve the large scale General Lotsizing and Scheduling Problem for Parallel Production Lines, as shown for example in Beraldi et al. (2008), Ferreira et al. (2009, 2012), Toso et al. (2009) and Helber & Sahling (2010).

Therefore, this work uses an MIP model to represent the programming and scheduling sugarcane harvesting front problem and proposes heuristic methods to solve this problem in real situations, comprising three integrated heuristics: a harvest block aggregation heuristic, a relax-and-fix constructive heuristic and a fix-and-optimize improvement heuristic. To the best of the authors' knowledge, no other work in the literature presents optimization approaches addressing this problem in this line of research.

Therefore, Section 2 describes the MIP to represent this problem, Section 3 presents the proposed heuristic methods to solve the sugarcane harvest planning problem, Section 4 compares the performance of the proposed heuristic methods, Section 5 illustrates and analyzes in detail a solution to the problem. Finally, Section 6 presents the final considerations of this study and discusses perspectives for future research.

2 Mathematical model

In order to model the problem, it is considered that the harvesting blocks $j = 1..B$, which have an estimated production of p_j, should be sequenced in the harvesting fronts $l = 1..F$ in a finite horizon time, divided into macro-periods $t = 1..P$. Each macro-period can be sub-divided into non-overlapping micro-periods of varying sizes. Each harvesting front has a specific definition of sub-periods. Set S_t describes the s micro-periods where $s = 1,..., \sum_{t=1}^{T}|S_t| = N$ (see Figure 1).

Set Bl_{jl} represents blocks j that can be harvested by the harvesting front l. Set Bs_{jt} represents the time-window, periods t, in which block j can be harvested. Harvesting $m \in M$ can be manual or mechanized, where F_m is the set of harvesting fronts that belong to set M. Therefore, in each block j, f_{jm} represents the fraction of the production block using harvest type m.

During the whole macro-period t, the harvesting fronts should meet the plant´s demand range $[mind_{mt}, maxd_{mt}]$ for each harvesting type m. Furthermore, there is a minimum amount of area to be released, vin_t, from set V_j, which represents the set of blocks that have fraction fi_j possible to be irrigated by vinasse.

Each front l has Nm_l machines (harvesters or loaders). A harvesting capacity of block j is given by col_j. The m harvesting machines work for Ht_m hours per day and have an identical working availability for all fronts l of K_t hours per macro-period t. The mode of transport considered is totally by road using a homogeneous fleet of Nt trucks, which work Htt hours per day. The fleet of vehicles also has a working availability of K_t hours per macro-period t. In addition, any truck can go to any harvesting front, as long as it follows a dynamic dispatching rule. Each block j has an associated transport capacity $transp_j$, which is a function of the distance from the plant and the conditions of the road network.

The capacity loss of the harvesting front during block changes is measured by the displacement time st_{ij}, between block i, where it is leaving from, to block j, where it is being moved to, which is calculated based on the distance between these blocks, $dist_{ij}$. The amount of vehicles with a flatbed trailer, Np, which enable harvesters to be transported (usually on a crawler harvester) over long distances, also affects the speed of the change of area. In order to make this change, not all the sugarcane from the block needs to be harvested, however a minimum amount, in tons, for block j and front l, bm_{lj} should be harvested so that the displacement of the front can be justified.

Among the models presented by Junqueira & Morabito (2017), this study considered the so-called 1B Model. This model has a trivial feasible solution, which is simply based on not producing (i.e., not harvest or transport), paying for the failure in the supply and for all the raw material left to be harvested in the next season. This material is called sugarcane left unharvested (ripe sugarcane harvested in the next season), which is a technical term from the field. Given this characteristic, feasible solutions can be easily obtained, potentializing, therefore the use of heuristic methods.

In the following paragraphs, this model is summarized to facilitate the reader's understanding of the solution methods proposed in the next section and so that the material of the article can be self-contained. Table 1 shows the decision variables. More details on the elements used by the model can be found in Junqueira & Morabito (2017).

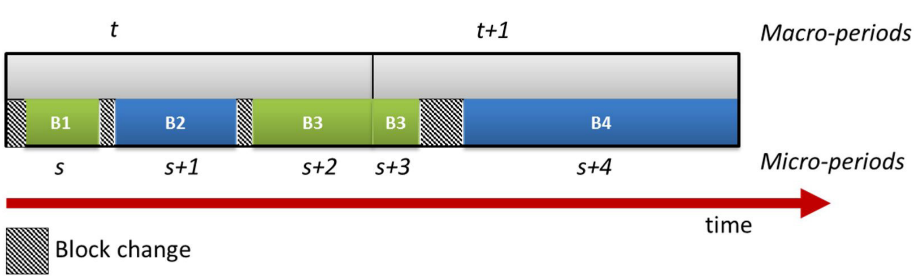

Figure 1. Relationship between macro- and micro-periods.

Table 1. Decision variables of the model.

Symbol	Definition
x_{ljs}	production of block j during micro-period s by the front l (in tons)
y_{ljs}	$\begin{cases} 1, \text{ if front } l \text{ is in block } j \text{ during micro-period } s \\ 0, \text{ otherwise} \end{cases}$
z_{lijs}	$\begin{cases} 1, \text{ if front } l \text{ moves from node } i \text{ to } j \text{ during micro-period } s \\ 0, \text{ otherwise} \end{cases}$
wm_{mt}	tons of milling lost from m *harvest* during period t
wb_j	tons of raw material left in block j

The MIP model is defined by:

$$Min\, mo\sum_{t=1}^{T} wm_{mt} + bs\sum_{j=1}^{B} wb_j + md\sum_{l=1}^{F}\sum_{j=1}^{B}\sum_{j=1}^{B} dist_{ij} z_{lij} \tag{1}$$

Subject to:

$$\sum_{l\in F_m}\sum_{j=1}^{B}\sum_{s\in S_t} x_{ljs} + wm_{mt} \geq mind_{mt} \qquad (t=1,\ldots,T),(m=man,mec) \tag{2}$$

$$\sum_{l\in F_m}\sum_{j=1}^{B}\sum_{s\in S_t} x_{ljs} \leq maxd_{mt} \qquad (t=1,\ldots,T),(m=man,mec) \tag{3}$$

$$\sum_{l\in F_m}\sum_{s=1}^{N} x_{ljs} + wb_j = p_j f_{jm} \qquad (j=1,\ldots,B), \quad (m=man,mec) \tag{4}$$

$$\sum_{m=man}^{mec}\sum_{l\in F_m}\sum_{j\in V_j}\sum_{s\in S_t} fi_j \frac{x_{ljs}}{TCH_j} \geq vin_t \qquad (t=1,\ldots,T) \tag{5}$$

$$\sum_{j=1}^{B}\sum_{s\in S_t} \frac{24}{col_{mj} Nm_l Ht_m} x_{ljs} + \sum_{i=1}^{B}\sum_{j=1}^{B}\sum_{s\in S_t} \frac{Nm_l}{Np} st_{ij} z_{lijs} \leq K_t \qquad (m=man,mec),\forall l\in F_m,(t=1,\ldots,T) \tag{6}$$

$$\sum_{m=man}^{mec}\sum_{l\in F_m}\sum_{j=1}^{B}\sum_{s\in S_t} \frac{24}{transp_{mj} NtHtt} x_{ljs} \leq K_t \qquad (t=1,\ldots,T) \tag{7}$$

$$x_{ljs} \leq \min\left(\frac{col_{mj} Nc_l Ht_m}{24}, \frac{transp_{mj} NtHtt}{24}\right) K_t y_{ljs} \qquad (m=man,mec),\forall l\in F_m,(j=1,\ldots,B),(t=1,\ldots,T),\forall s\in S_t \tag{8}$$

$$x_{ljs} \geq bm_{lj}\left(y_{ljs} - y_{ljs-1}\right) \quad (m=man,mec),\forall l\in F_m,(j=1,\ldots,B),(s=1,\ldots,N) \tag{9}$$

$$\sum_{j\in\left(Bs_{jt}\cap Bl_{jl}\right)} y_{ljs} = 1 \qquad (l=1,\ldots,F),(t=1,\ldots,T),\forall s\in S_t \tag{10}$$

$$y_{lis-1} = \sum_{j=1}^{B} z_{lijs} \qquad (l=1,\ldots,F),(i=1,\ldots,B),(s=2,\ldots,N) \tag{11}$$

$$\sum_{i=1}^{B} z_{lijs} = y_{ljs} \qquad (l=1,\ldots,F),(j=1,\ldots,B),(s=1,\ldots,N) \tag{12}$$

$$y_{ljs-1} \geq y_{ljs} \qquad (l=1,\ldots,F),(j=1,\ldots,B),(t=1,\ldots,T),\forall s\in\left(S_t \setminus S0_t\right) \tag{13}$$

$$x_{ljs} \geq 0 \qquad (l=1,\ldots,F),(j=1,\ldots,B),(s=1,\ldots,N) \tag{14}$$

$$y_{ljs} \in \{0,1\} \qquad (l=1,\ldots,F),(j=1,\ldots,B),(s=1,\ldots,N) \tag{15}$$

$$z_{lijs} \geq 0 \qquad (l=1,\ldots,F),(i=1,\ldots,B),(j=1,\ldots,B),(s=1,\ldots,N) \tag{16}$$

$$wm_{mt} \geq 0 \qquad (t=1,\ldots,T),(m=man,mec) \tag{17}$$

$$wb_j \geq 0 \qquad (j=1,\ldots,B) \tag{18}$$

The Objective Function 1 assesses the impact of the milling failure costs, sugarcane left unharvested and also the displacement of harvesting fronts, which is also considered, although it is of second order if compared to the other two. Slack variables measure the tons of lost milling, Constraints 2, and for tons of raw material not harvested left in the field, Constraints 4. There is a cost per hour or per ton, mo and bs, respectively, for each of the parameters. Parameter *md* represents the transport cost of a front per km.

Constraints 2 to 4 ensure the mass balance, adjusting the field production according to the plant´s demand. Constraints 2 and 3 are related to the minimum and maximum milling demand per period, ensuring that the amount of harvested and transported raw material of a specific kind of harvesting is higher than the amount demanded for the period. Constraints 4 limit the harvest and transport to the availability of raw material in the block and is, therefore, related to the field production, considering the kind of harvesting of the front and the block. Constraints 5 determine the minimum amount of vinasse area to be released at each macro-period *t*, taking into account the amount of irrigable area in the block, where TCH_j represents productivity (in tons) per hectare for block *j*.

Constraints 6 and 7 consider the harvesting and transport capacity resources. Constraints 6 relate the time spent producing harvest resources, as well as the time spent on transporting equipment from one area to another with the total time available in the period. The resource production time takes into account the block performance characteristics, as well as the agronomic suitability for the harvest during the period. The time for transporting the equipment when moving from one area to another takes into account the time spent on this move, as well as the number of vehicles with a flatbed trailer available for this operation. Constraints 7 address the transportation resources, whose production potential is considered per block. In this case, the time spent on moving the front is not inserted, because when moving the area these resources can transport the production of the areas under operation or they are idle consuming stock on the roads at the industrial unit. In addition, as there are no specific trucks for each harvesting front as they can go to any front, this capacity balance can be done only for all periods *t*, and not for all fronts *l* and periods *t*, as in constraint 6 where the amount of harvesters is defined per harvesting front.

Constraints 8 to 9 couple variables x_{ljs} and y_{ljs}. Constraints 8 ensure that when there is production in block *j* by the harvesting front *l* during micro-period *s*, the front is positioned at the same place and time. In the same way, for the opposite situation, when the front is not positioned, there is no production of the block. It is important to mention that the upper limit of x_{ljs} was considered the minimum between the harvesting and transport capacity. It is expected that the harvesting capacity is the most restrictive, unless there is a front with a higher capacity than the whole fleet. Inequalities 9 are constraints of the minimum lot and define the minimum amount of raw material to be harvested, whereas Equations 10 ensure that front *l* will be in only one block *j* during micro-period *s*. Using parameter Bs_{jt}, these constraints impose that the harvest occurs in blocks *j* allowed by the time windows, that is during macro-periods *t*. In addition, using parameter Bl_{jl}, these equations define blocks *j* that a harvesting front *l* can harvest. This happens when it is necessary to sectorize one of the fronts. It is worth highlighting that $y_{ljs} = 0$ are previously fixed for micro-periods *s* that are out of the time-window of block *j* (Bs_{jt}), as well as for those fronts *l* that cannot be harvested (Bl_{jl}).

Constraints 11 and 12 define the movement of the front by variable z_{lijs}, consistent with the positions of the front during micro-period *s* (y_{ljs}) and during the previous micro-period *s*-1 (y_{lis-1}). Constraints 13, although redundant in terms of obtaining an optimal feasible solution, establish that the idle micro-periods occur only at the end of the macro-period and, therefore, eliminate equivalent (symmetric) solutions. Constraints 14, 15, 16, 17 and 18 define the non-negative variables x_{ljs}, z_{lijs}, wm_{mt} and wb_j, as well as the binary variable y_{ljs}.

3 Proposed solution methods

The exact resolution of an actual problem based on the model used in this study may not feasible due to the size of the problem. The company studied, which is a medium-sized plant, had for the crop studied: five harvesting fronts, eight months of harvesting (macro-periods), 200 effective harvest days and an average permanence time of three days of the front per block. Therefore, there are 80 micro-periods and 330 harvesting blocks, which result in 132,000 integer variables.

The first step of the proposed method was to aggregate the harvesting blocks, so that variables such as the distance of the block from the plant and the harvesting potential were not de-characterized. The second step involved proposing heuristic methods based on MIP, such as the relax-and-fix method to construct a good feasible initial solution. The third step entailed using the fix-and-optimize method to try to improve the solution constructed in step 2. Figure 2 illustrates the proposed heuristic method.

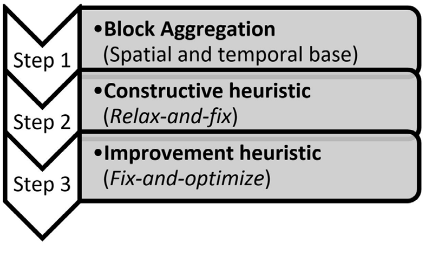

Figure 2. Proposed heuristic method.

A simple alternative heuristic would be to solve the original problem using an optimization package to solve the model within a limited maximum time, even if an optimal solution is not reached. In this case, it might also be appropriate to use a block aggregation heuristic (step 1). Another option would be to solve only steps 1 and 2.

3.1 Block aggregation

First, the aggregated block cannot disregard the time windows for each harvesting block, represented by $Bs_{j't}$ in the model. These windows can also be characterized by allowing (1), or not (0), the harvest in a given month (macro-period). If the crop is divided into eight macro-periods; for example, each block could have a temporal pattern of |0|0|0|1|1|1|0|0|. This code means that a specific block cannot be harvested during the three first macro-periods, nor during the two last ones. Harvesting is allowed only from the fourth to the sixth macro-periods. Therefore, there may be *P* temporal patterns, each one characterized by allowing (1), or not (0), the harvest in a given macro-period *t* (PT_{pt}). Thus, BT_p represents the set of blocks *j'* that belong to temporal pattern *p* where $Bs_{j't} = PT_{pt}$.

In this study, 10 patterns were detected, as shown in Table 2. Pattern 10 refers to areas yet to be planted. Patterns 1 and 2 are areas planted with late varieties, for which harvesting is recommended during the last two months of the season. Patterns 3, 4, 5 and 6 are areas planted with average varieties, whereas patterns 7, 8 and 9 are areas planted with earlier varieties, whose recommendation is to harvest them during the first three months of the crop. It is worth mentioning that pattern |1|1|1|1|1|1|1|1| is the one that has the greatest degree of freedom to fit the area´s schedule in any period, and can thus act as a balancing factor for the harvesting and transportation capacities. After determining the ideal harvesting period for the area, the agricultural team tries to plant varieties that are adequate for the production environment and whose LTIU is compatible.

As well as the temporal pattern, usually the harvest blocks considered in the plants do not exceed the farm limits in spatial terms. However, if the geographical coordinates of the block *j'* ($X_{j'}, Y_{j'}$), are known, it is possible to exceed these limits and then address a wider geographical region. In the case of the company studied here, the operational area of the plant was divided into reticulates of 10 km each, resulting in a perimeter of 68 km wide by 71 km high. Thus, square *q* is defined by the set of coordinates $\{(X_{qmin}, Y_{qmin}), (X_{qmin}, Y_{qmax}), (X_{qmax}, Y_{qmin}), (X_{qmax}, Y_{qmax})\}$, given that point ($X_{qmin}, Y_{qmin}$) represents the square's minimum coordinate *q* and also that point (X_{qmax}, Y_{qmax}) represents the maximum coordinate. For block *j'* to belong to square *q*, the following conditions should be met: $X_{qmin} \leq X_{j'} < X_{qmax}$ e $Y_{qmin} \leq Y_{j'} < Y_{qmax}$. Therefore, set BE_q groups blocks *j'* which belong to square *q*.

Graph 1 shows the geographical distribution of the original and the aggregated harvesting blocks. The plant is located at coordinate (0,0). The original blocks are shown in grey. For the aggregated blocks, each kind of marker represents a temporal pattern. The colors for the aggregated blocks distinguish the different patterns that belong to the same variety.

It is clear from Graph 1 that although there are some points where the original block coincides with the aggregated one, (square X=[-40,-30] and Y=[0,10]), particularly near the plant, it can be observed that various blocks were grouped into one (square X=[-10,0] and Y=[0,10]). Moreover, in this latter square, it can be seen that there are several period patterns, yet they do not repeat themselves within it. There are a few other cases of having multiple patterns within the same square (for example, X=[10,20] andY=[-20,-10]).

Therefore, the aggregated block *j*, consists of the set of blocks *j'* where $X_{qmin} \leq X_{j'} < X_{qmax}$, $Y_{qmin} \leq Y_{j'} < Y_{qmax}$ and $Bs_{j't}=PT_{pt}$, that is, $BA_j = BA_{qp} = BE_q \cap BT_p$. For example, for $j'=1,...,10$, $q=\alpha$, β and p=A, B, there is $BE_\alpha = \{1,3,7,9\}$, $BE_\beta = \{2,4,5,6,8,10\}$ $BT_A = \{2,4,7,8,9,10\}$ $BT_B = \{1,3,5,6\}$ Given this, four blocks are formed, j = 1,2,3,4, that is,

Table 2. Period patterns (I A1).

	Pattern	P1	P2	P3	P4	P5	P6	P7	P8
1	|0|0|0|0|0|0|1|1|	0	0	0	0	0	0	1	1
2	|0|0|0|0|1|1|1|1|	0	0	0	0	1	1	1	1
3	|0|0|0|1|1|0|0|0|	0	0	0	1	1	0	0	0
4	|0|0|0|1|1|1|0|0|	0	0	0	1	1	1	0	0
5	|0|0|1|1|1|1|0|0|	0	0	1	1	1	1	0	0
6	|0|0|1|1|1|1|1|0|	0	0	1	1	1	1	1	0
7	|0|1|1|1|0|0|0|0|	0	1	1	1	0	0	0	0
8	|1|1|1|0|0|0|0|0|	1	1	1	0	0	0	0	0
9	|1|1|1|1|0|0|0|0|	1	1	1	1	0	0	0	0
10	|1|1|1|1|1|1|1|1|	1	1	1	1	1	1	1	1

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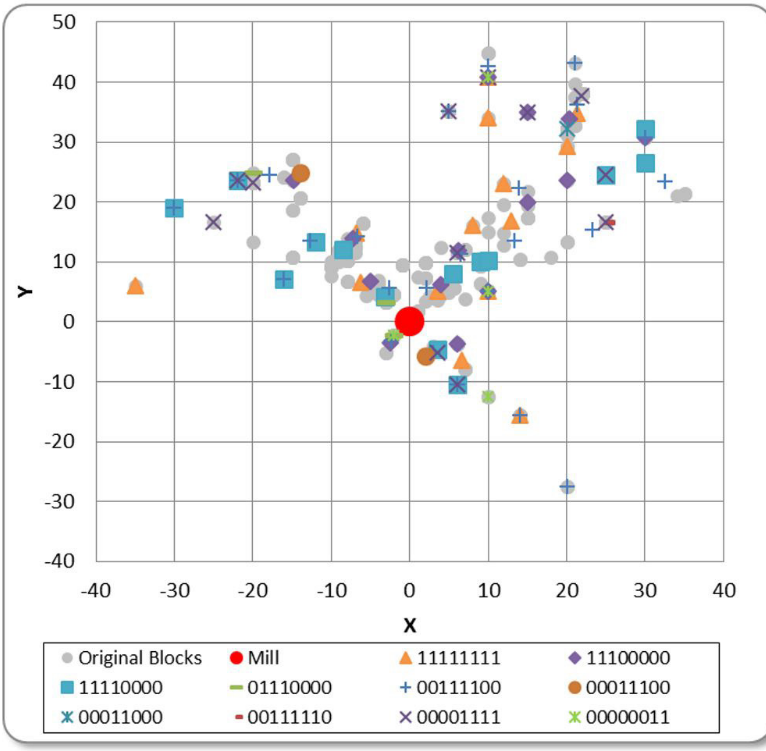


Graph 1. Geographical distribution of harvesting blocks.

$BA_1 = BE_\alpha \cap BT_A = \{7,9\}$, $BA_2 = BE_\alpha \cap BT_B = \{1,3\}$, $BA_3 = BE_\beta \cap BT_A = \{2,4,8,10\}$, $BA_4 = BE_\beta \cap BT_B = \{5,6\}$.

Once the aggregated block is formed, the aggregated characteristics based on the unit of area *j'* should be determined, which would be: the production, harvesting potential, transport potential and geographic coordinates. The production for the aggregated block would be the sum of $p_{j'}$, as well as $col_{mj'}$, $transp_{mj'}$, $X_{j'}$ and $Y_{j'}$ are determined by the production weighted average, according to Equations 19 to 23.

$$p_j = \sum_{j' \in BA_j} p_{j'} \tag{19}$$

$$col_{mj} = \frac{\sum_{m=man}^{mec} \sum_{j' \in BA_j} col_{mj'} * p_{j'}}{\sum_{j' \in BA_j} p_{j'}} \tag{20}$$

$$transp_{mj} = \frac{\sum_{m=man}^{mec} \sum_{j' \in BA_j} transp_{mj'} * p_{j'}}{\sum_{j' \in BA_j} p_{j'}} \tag{21}$$

$$X_j = \frac{\sum_{j' \in BA_j} X_{j'} * p_{j'}}{\sum_{j' \in BA_j} p_{j'}} \tag{22}$$

$$Y_j = \frac{\sum_{j' \in BA_j} Y_{j'} * p_{j'}}{\sum_{j' \in BA_j} p_{j'}} \tag{23}$$

In the sample presented at the beginning of this section, the number of blocks was reduced from 330 to 93 in the company studied. Therefore, the number of integer variables becomes 37,200 rather than 132,000. However, care should be taken when defining the size of the square, because on the one hand, the larger its size, the higher the reduction in the number of problem variables; on the other hand, squares that are too big may hide the effect of the area change. Therefore, it is important for a planner, who knows the areas of the plant well, to help determine the aggregated harvesting blocks.

3.2 Relax-and-fix constructive heuristic

As the *relax-and-fix* heuristic is able to generate an initial feasible solution (constructive heuristic), its execution follows the formation of aggregated blocks. The literature suggests various strategies for decision variable decomposition for the relax-and-fix method to solve the GLSPPL; among them are those that use the period (macro-periods) and resources (harvesting fronts). Moreover, a composition of both is possible. By using a relax-and-fix strategy based on the period, at least two forms are possible: forward, from the first to the last period, or backward, from the last to the first.

Let *tt* be an auxiliary index identical to *t*, which represents the macro-periods. Thus, Figure 3 shows a proposed relax-and-fix algorithm for the resolution of the proposed MIP using a decomposition strategy of the forward temporal variable y_{ljs}. Figure 4, shows the same type of algorithm, with a backward temporal strategy.

In these two cases, the number of macro-periods within each sub-problem could be reduced. In the example discussed in Section 3.1, the 80 micro-periods were reduced to 10 for each sub-problem. Therefore, the number of integer variables was reduced to 4,650; approximately 88% (37,200 variables) lower than the problem with aggregated blocks and 97% lower than the original problem (137,000 variables). Although using this approach entails solving the subproblem eight times, this size of GLSPPL can be dealt with much better computationally.

Let *ll* be an auxiliary index identical to *l*, which represents the harvesting fronts (resources). Thus, Figure 5 shows a proposed *relax-and-fix* algorithm to solve the proposed mathematical programming model with a strategy for variable y_{ljs} decomposition per harvesting front. In the example discussed in Section 3.1, the five fronts are reduced to one in each subproblem. Therefore, the number of integer variables is reduced to 7,440, approximately 67% (37,200 variables) lower than the problem with aggregated blocks and 95% lower than the original problem (137,000 variables). Although using this approach entails solving the subproblem five times, this size of GLSPPL can be dealt with much better computationally. Compared with the previous strategy, the size of the subproblem for the temporal partition is smaller; however, partitioning by fronts allows the problem to be solved in less number of times.

Relaxation of integer variables (y_{ljs});
For *tt* = 1 until *T*, do:
Treat variables *y* from period *tt* ($y_{ljs} \in S_{tt}$) as integers;
Set values of $y_{ljs} \in Bl_{jl}$, $y_{ljs} \in Bs_{jtt}$ and $y_{ljs} \in S_{tt}$;
Solve the GLSPPL;
Set the obtained values of *y* for period *tt* ($\mathbf{y}_{ljs} \in \mathbf{S}_{tt}$);

Figure 3. Relax-and-fix forward temporal algorithm.

Relaxation of integer variables (y_{ljs});
For *tt* = *T* until 1, do:
Treat variables *y* from period *tt* ($y_{ljs} \in S_{tt}$) as integers;
Set values of $y_{ljs} \in Bl_{jl}$, $y_{ljs} \in Bs_{jtt}$ and $y_{ljs} \in S_{tt}$;
Solve the GLSPPL;
Set the obtained values of *y* for period *tt* ($\mathbf{y}_{ljs} \in \mathbf{S}_{tt}$);

Figure 4. Relax-and-fix backward temporal algorithm.

Relaxation of integer variables (y_{ljs});
For *ll* = 1 until *F*, do:
Treat variables *y* from front *ll* (y_{lljs}) as integers;
Set values of $y_{lljs} \in Bl_{jll}$ e $y_{lljs} \in Bs_{jt}$;
Solve the GLSPPL;
Set the obtained values of *y* for front *ll* (y_{lljs});

Figure 5. Relax-and-fix algorithm per harvesting front.

Fix integer variables of a feasible initial solution (y_{ljs});
Treat variables *y* of period *tt* = *1* ($y_{ljs} \in S_{tt}$) as integers;
For *tt* = 2 until *T*, do:
Treat variables y for period *tt* ($y_{ljs} \in S_{tt}$) as integers;
Fix values of $y_{ljs} \in Bl_{jl}$, $y_{ljs} \in Bs_{jtt}$ and $y_{ljs} \in S_{tt}$;
Solve GLSPPL;
Fix the obtained values of *y* for period *tt-1* ($y_{ljs} \in S_{tt-1}$);

Figure 6. Forward temporal fix-and-optimize algorithm with overlapping.

3.3 Fix-and-optimize improvement heuristic

After performing the relax-and-fix method, a good feasible initial solution is expected to be found. In order to improve it, the fix-and-optimize method is proposed. In the same way as the relax-and-fix, the fix-and-optimize method uses a decomposition of variable y_{ljs} to solve the GLSPPL based on the strategies described previously: temporal, per front (resource) or per block (product). For the *fix-and-optimize* option in particular, the *overlapping* techniques are an interesting option, as variables that are not integers and are part of the subproblem will have fixed values. By using overlapping, solutions different from those obtained from the constructive heuristic can be sought. Figure 6 shows an algorithm for the forward temporal fix-and-optimize improvement model with two-periods overlapping. In the example discussed in Section 3.1, the size of this subproblem would be similar to twice the relax-and-fix case with temporal partition of integer variables, i.e., there would be 9,300 variables and it should be solved seven times.

4 Comparing methods used

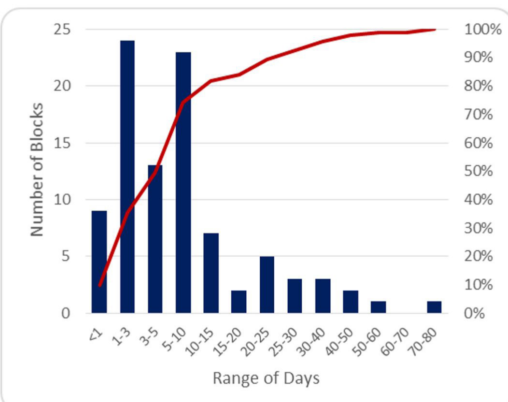
The heuristic methods proposed in Sections 3.1, 3.2 and 3.3, developed for the model in Section 2 were combined and tested in this section using the harvest planning data for the company studied. Therefore, Section 4.1 presents the company studied, describing the input data for this company, and Section 4.2 shows the experiments carried out during this study.

4.1 Company studied and data collected

The plant studied is located in the west of the State of São Paulo, Brazil, the last area of the state to be expanded. The plant was founded less than 10 years ago. The 2013/2014 harvest had 10,500 t/day; i.e., 2,100,000 t milled during the harvesting season. In terms of land structure, the plant is formed by large farms, enabling it to operate using large harvesting blocks which are not geographically dispersed.

The topography is characterized by smooth undulations, providing a high level of mechanization in the area. Therefore, the harvest is fully mechanized and the harvest structure is all its own.

Data were collected from this plant over a period of approximately three years through consultancy work focusing on harvesting and transportation logistics developed by one of the authors. During this period, insightful information was obtained, at that time foreseen for the then future harvest of 2013/2014. The information obtained was about: the harvesting and transport potential, milling capacity, amount of raw material per area and availability of resources in terms of time and quantity. This survey was carried out in mid 2012.



Graph 2. Histogram of the fronts' dwell time.

In this section, we present the main aspects concerning the model's input data applied to the company studied after using the aggregation heuristic (Section 3.1) called sample A1. More details can be found in Junqueira (2014). First, all the harvesting blocks are mechanizable and the harvest will be carried out using three harvesting fronts with five harvesters and two fronts with four harvesters. Not including the time for routine stops for: maintenance, refuelling, shift changeover, meal times and other operational breaks, the harvesters must work 14 hours per day according to the company's target for the harvest. The same goes for the hours worked of the trucks, which was defined by the company for 16.6 hours worked as a goal.

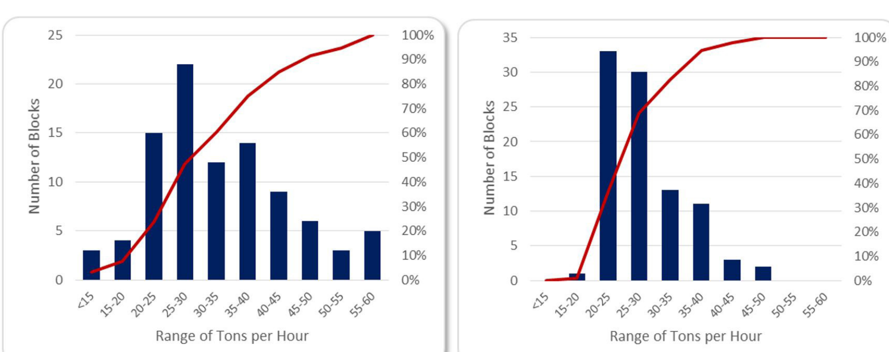
To make it easier to visualize the characteristics of the blocks, Table 3 shows the basic descriptive statistics of the characteristics of the aggregated blocks.

Graph 2 complements the characterization presenting a histogram of the dwell time of the front in the harvesting blocks. It is worth mentioning that all the histograms in this study contain a bar chart for each *x* axis class showing the frequency of occurrence of the analyzed variable quantified on the main *y* axis (in this case the number of blocks). It also shows a line graph representing the cumulative percentage of the classes quantified in the secondary *y* axis. Graph 3a shows the histogram of the harvest potential and Graph 3b depicts the transport potential.

By analyzing the size of the block in Table 3 and the dwell time of the front in Graph 2, it is clear that although there are some small blocks, i.e. with less than one day of dwell time, they are not significant as they represent approximately 10% of the plant's blocks and

Table 3. Descriptive statistic of the aggregated blocks' characteristics.

	Block Size (t)	Harvest (t/h)	Transport (t/h)
Minimum	267	7	19
Average	22,492	33	28
Maximum	177,583	60	46



(a) **(b)**

Graph 3. Histogram of the potential of (a) harvesting (b) transportation.

less than 1% of the amount of the raw material available. On the other hand, there is a considerable amount of large blocks (dwell time of more than 5 days in the fronts), representing approximately 30% of the blocks and 82% of the raw material available. The weight of these large blocks shifts the average to approximately 10,000 t above the median. This characteristic reduces the complexity to obtain a good solution to the problem because it reduces the need to change the area of the harvesting fronts, and is able to stay long periods of time in large blocks with negligible capacity losses due to the front moving.

Graph 2 also shows that in less than 10% of the blocks, the dwell time is less than one day and in about 30%, this time is less than three days. Therefore, the number of micro-periods adopted for this sample was ten per front in a monthly period. This is equivalent to an area change of the harvesting front every three days. This definition is extremely critical for defining the model size and, given the data presented, it seems quite reasonable as three days of the front´s dwell time in the block is below the mean and the median.

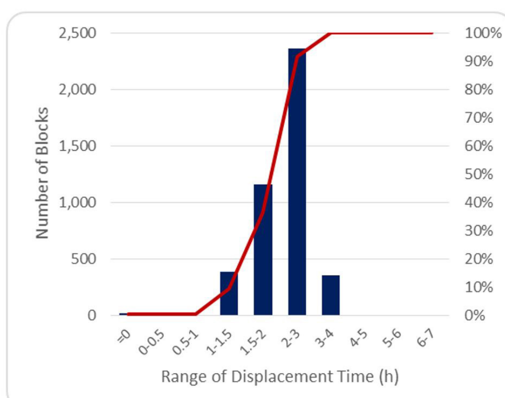
When analyzing the harvest potential in Table 3 and Graph 3a, it can be observed that there was a large dispersion, with very low potentials (varying between 7 and 60 tons per hour). In this particular case, the low harvest potential can be related, mainly, to the drought that affected the harvests in 2010/2011, 2011/2012 and 2012/2013. Considering a harvester working 14 hours per day, its production varies from 100 to 840 tons per day. For a production of 10,500 tons per day, and considering that all harvesters are working in minimum production conditions, 105 units are required, yet in the best conditions, only 13 would be necessary. In average conditions, 22.7 harvesters are needed, and the plant has 23 in total of its fronts. Harvest capacity constraints allow a balance between the potential of the available areas, the number of harvesters available, and the time of movement of the fronts.

Similarly to the harvest, analyzing the transportation potential in Table 3 and Graph 3b, a lower dispersion can be noticed that the harvesting potential, varying from 19 to 46 tons per hour. In the case of a truck working 16.6 hours per day, the production varies from 318 to 840 tons per day. For a production of 10,500 tons per day, if all trucks are in a minimum production condition, it would require 33 units, however in the best condition, only 13 are required. In an average condition, 22.7 trucks would be needed, and the plant has 25 in total. Moreover, transport capacity constraints allow for a balance between the potential of the available areas and the amount of trucks available.

The distance between the blocks was estimated based on the Euclidian distance between their coordinates. The Euclidian distances were corrected by a percentage of 30%. As this displacement forms a symmetric matrix, only one side of the matrix was considered and the diagonal was excluded, which only has values equal to zero

From the distances between the blocks, the traveling time was calculated estimating a speed of 40 km/h for the transport vehicles on the way out, a time of 30 min for loading and unloading or embarkation and disembarkation of the harvesters of 30 min, as well as an efficiency of 85% for this operation. This efficiency represents the cases where there are more harvesters than vehicles with flatbed trailers and it was necessary for the harvester to wait for the return trip of another harvester so that it could be transported. Therefore, Graph 4 shows the histogram of the displacement time between harvesting blocks.

Finally, Table 4 shows the parameters analyzed, per macro-period. For the harvest, eight macro-periods were defined which are related to the month with 24-hr shifts.



Graph 4. Histogram of displacement time between blocks.

Table 4. Definition of parameters per macro-period.

Macro-period	Capacity (h)	Minimum Demand (t)	Maximum Demand (t)	Expected Demand (t)
P1	496	212,717	221,399	217,058
P2	632	271,144	282,211	276,678
P3	634	271,659	282,747	277,203
P4	684	293,474	305,452	299,463
P5	684	293,474	305,452	299,463
P6	684	271,659	282,747	277,203
P7	632	271,144	282,211	276,678
P8	384	164,642	171,362	168,002

Capacity refers to the hours available for the harvesting fronts and transportation, considering the actual harvest days; that is, not including the waiting time of the plant for maintenance. The expected demand is calculated considering the hours available in the macro-period and the hourly milling, which in the case of 10,500 tons per day, is 437.5 tons per hour. The minimum and maximum demands were calculated for the model case, with a margin of 2% above or below the expected milling.

Knowing the demands of milling by macro-period and knowing the amount of raw material per temporal pattern, previous balancing can be carried out to identify the unfeasibility for solving the proposed models. Table 5 shows that this preliminary balancing was done using a simple heuristic. To begin with, the first macro-periods were met with the earliest temporal patterns, then the middle and later patterns. If for some period raw material was not enough, it is fulfilled with the pattern for the areas to be planted.

By analyzing Table 5, it can be observed that there is feasibility in terms of the balance between milling and raw material available considering the temporal patterns. In addition, it can be seen that the areas to be planted should supply the lack of raw materials during macro-periods 6, 7 and 8 when they are middle and later.

4.2 Computational implementation and analysis of the experiments

The model in Section 2 was implemented using the GAMS software, version 24.1.3; and the CPLEX solver version 12.5.1.0 was used to solve the A1 sample in a high-performance computer equipped with: Intel i7-3770 processor with eight cores and 16GB RAM memory. It is worth pointing out that this sample entails using 30 thousand variables and three million constraints.

Table 6 describes the experiments carried out using the sample presented in Section 4.1, to which the aggregation heuristic (presented in Section 3.1) was applied, using the model from Section 2, with and without the constructive improvement heuristics presented in Sections 3.2 and 3.3. This table is organized into 5 blocks of columns. The first block refers to the results obtained by executing the model: the objective function value, optimality gap and run time. The second block shows the configuration of the GAMS/CPLEX parameters used in each experiment: if the RINS heuristics, Feasibility Pump and Local Branching were on; if the basic CPLEX Presolve processes and cutting planes were on; and the run time limit (reslim) in the experiments in which the heuristics were not executed. The third block describes the design of the relax-and-fix constructive heuristic using the following items: if the partition in the subproblems was temporal, based on the resource (harvesting fronts) or a combination of both; for the case of temporal, if the strategy used was forward or backward; if there was overlapping in any of the partitions; and the run time limit of each subproblem. The fourth block deals with the fix-and-optimize improvement heuristic configuration, identifying the following configurations: if the partition into subproblems was done based on the blocks or temporal forward; if there was overlapping in any of the two possible partitions; and the run time limit of each subproblem. The fifth block addresses a change made to the model, treating variable *z* as real or integer. Other parameters adopted that did not vary throughout the experiments were: the automatic choice of the CPLEX of the number of processor cores; the maximum number of iterations (*iterlim*) of 10,000,000; the memory allocation (*workmem*) of 30GB; and the acceptable optimality gap zero to complete the execution (*optcr*).

First, the sample was solved using the model without the constructive and improvement heuristics; i.e., using only the model limited by time. Experiments 1,

Table 5. Preliminary balancing.

Period	**11111111**	**11100000**	**11110000**	**01110000**	**00111100**	**00111110**	**00011000**	**00011100**	**00001111**	**00000011**	**Total**
1		217,058									**217,058**
2		106,568	155,844	14,266							**276,678**
3				16,510	260,293						**277,203**
4					299,463						**299,463**
5					149,876	5,277	8,170	13,313	122,827		**299,463**
6	234,370								42,833		**277,203**
7	256,186									20,492	**276,678**
8	168,002										**168,002**
Total	658,558	323,626	155,844	30,776	710,031	5,277	8,170	13,313	165,660	20,492	2,091,747

Table 6. Computational experiments using the model.

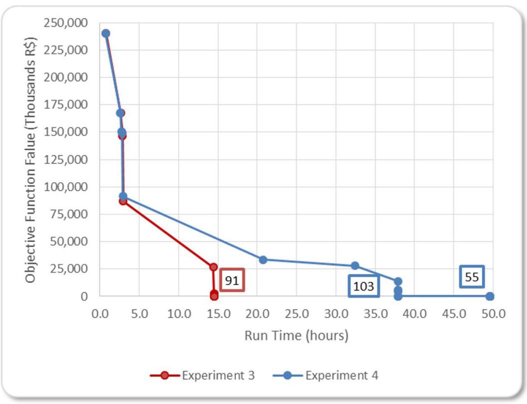
	Results			Constructive (Relax&Fix)						Improvement (Fix&Optimize)										
Experiments	**Objective function value (in thousands)**	***Gap* (%)**	**Run time (hh:mm)**	**RINS**	**Feasibility Pump**	**Local Branching**	**Presolve**	**Cuts**	**Reslim (1000s)**	**Temporal**	**Forward**	**Backward**	**Front**	**Overlapping**	**Reslim (1000s)**	**Block**	**Temporal (forward)**	**Overlapping**	**Reslim (1000s)**	**Model Var z**
1	38,926	99.98	14:30	X	X	X	X	X	52.2											R
2	138,196	100.00	14:30				X	X	52.2											R
3	91	92.82	14:31	X			X	X	52.2											R
4	55	88.16	50:00	X			X	X	180											R
5	21,170	99.97	05:23	X			X	X		X	X				10.8					R
6	4,212	99.84	24:13	X			X	X		X		X			10.8					R
7	28,134	99.98	08:15	X			X	X		X		X		X	10.8					R
8	21,170	99.97	08:00	X			X	X		X	X	X			10.8					R
9	21,982	99.97	96:37	X			X	X		X	X	X	X	X	10.8					R
10	4,212	99.84	24:30	X			X	X		X		X			10.8					Int
11	28,315	99.98	09:26	X		X	X	X		X		X			10.8					R
12	28,315	99.98	10:02	X	X		X	X		X		X			10.8					R
13	4,165	99.84	24:10	X		X	X	X		X		X			10.8					R
14	6,005	99.89	23:51			X	X	X		X		X			10.8					R
15	3,758	99.83	23:59				X	X		X		X			10.8					R
16	40,959	99.98	09:37				X			X		X			10.8					R
17	No solution		06:12			X		X		X		X			10.8					R
18	59	88.92	50:54				X	X		X		X		X	10.8		X	X	21.6	R
19	59	88.92	49:15				X	X		X		X			10.8		X	X	21.6	R
20	159	95.88	24:44				X	X		X		X			10.8	X		X	2.7	R

2 and 3 compared the CPLEX parameters, showing that the feasibility pump heuristics, emphasizing solution quality and local branching did not help to improve the quality of the solution, as shown in Experiment 1. However, the RINS heuristic showed important results for the solution quality, for example when Experiment 2 is compared to Experiment 3, although its *Gap* still remains high. Among the three solutions, it is worth mentioning that the quality of Experiment 3 is reasonably good, because although the objective function value is greater than zero, the amount of sugarcane lacking is insignificant. The objective function value is based on the sugarcane surplus for the following year (sugarcane left unharvested) in a small volume (18,232 tons), representing less than two actual days of milling. As Experiment 4 was the most successful, it is analyzed in more detail in Section 5.

For the next experiments, which involve applying the combinations of the heuristics proposed in Sections 3.2 and 3.3 to the model, the option taken was to use the configuration with RINS, pre-processing and bound cutting plane, emphasizing the feasibility pump in optimality and local branching off. It is worth mentioning that the solutions of experiments 18, 19 and 20 are comparable to those of experiments 3 and 4, with good quality, since the solution reached met the milling demand and little sugarcane left unharvested remained. More details on the tests performed can be found in Junqueira (2014).

Concerning the computational times, Graph 5 shows the evolution of the objective function values for experiments 3 and 4 as a function of the run time. By observing this graph, it can be seen that with approximately 38 hours of execution, experiment 4 obtained a good solution, possibly indicating a moment of interruption in the execution of the GAMS/CPLEX. The same did not occur with experiment 3, which obtained the final solution value very close to the run time limit.

Therefore, it can be claimed that in practice experiments 3, 4, 18, 19 and 20 presented solutions with acceptable results. These solutions can be considered good, as they were affected only by the raw material that could not be harvested in the current year; in these cases there was no shortage of raw material. Although Experiment 4 presented the best quality solution, Experiment 3 had already presented a reasonably good one in a much shorter run time (see Graph 5). On the other hand, the proposed heuristics, obtained good results when combined (constructive + improvement), but it cannot be said that they performed better than the CPLEX with the equivalent limited run time. The quality of the results for experiments 18 and 19 were equivalent to those of Experiment 4, with similar run times.



Graph 5. Objective function × Run time.

5 Analysis of the solution obtained

The solution analyzed in this section refers to the one found in Experiment 4 using sample A1 studied in the previous section and the model from Section 2, as this solution presented the best quality among those considered good. Table 7 shows an analysis of the milling. This plan meets the minimum milling constraint for all the macro-periods. Moreover, in periods P1, P2, P7 and P8, the harvest was better than the minimum milling. The plan does not exceed the maximum milled amount, reaching its limit at P7 and P8.

From the total of 2,091,747 tons of sugarcane available, there was a surplus of 11,055 tons of sugarcane left unharvested (3,450 t from block b37 and 7,604 t from block b75). This solution still had industrial capacity to absorb this milling; however there was no capacity available for harvesting and transport resources to do so. Table 8 shows an analysis of the harvesting and transport capacity resources. The table shows the amount of hours available for the macro-period and the amount used by the harvesting and transportation resources. In the case of harvesting, the use of the capacity was split into two items: operation, representing the time the resources were in fact working; and displacement,

Table 7. Milling analysis.

Macro-period	Production (t)	Minimum milling (t)	Above the minimum milling (t)	Maximum milling (t)	Below maximum milling (t)
P1	220,603	212,717	7,886	221,399	797
P2	276,252	271,144	5,107	282,211	5,960
P3	271,659	271,659	0	282,747	11,088
P4	293,474	293,474	0	305,452	11,979
P5	293,474	293,474	0	305,452	11,979
P6	271,659	271,659	0	282,747	11,088
P7	282,211	271,144	11,067	282,211	0
P8	171,362	164,642	6,720	171,362	0
General Total	2,080,692	2,049,912	30,780	2,133,582	52,890

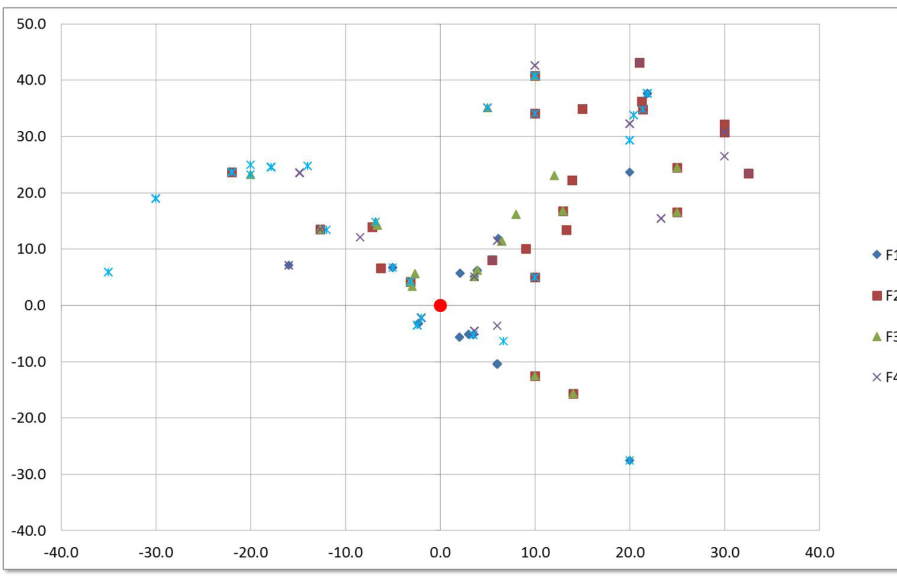
Table 8. Analysis of capacity.

	P1	P2	P3	P4	P5	P6	P7	P8	TOTAL
Available	496	632	634	684	684	634	632	384	**4,781**
Transport	414	523	615	659	616	545	632	384	**4,389**
% Surplus	17	17	3	4	10	14	0	0	**8**
Harvest									
Total Operation	487	610	617	666	670	620	522	308	**4,500**
Displacement	9.0	22.5	16.1	18.3	14.5	14.0	33.8	16.3	**145**
Total	496	632	634	684	684	634	556	324	**4,645**
% Displacement	2	4	3	3	2	2	6	5	**3**
% Surplus	0	0	0	0	0	0	12	16	3

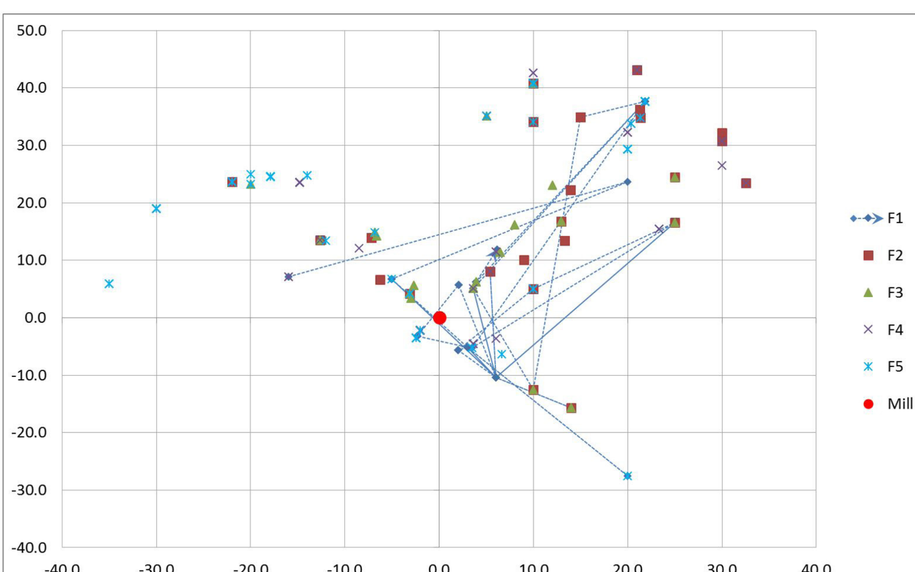
representing the time spent on moving the resources from one area to another.

By analyzing Table 8, it can be seen that macro-periods P7 and P8 required more from the transport resources, whereas from P1 to P6 required more from the harvesting resources. Overall, there was a resource slack: 8% for transportation and 3% for harvesting. From the total time of the harvesting resources, about 3% of the time was spent on displacement and was more significant in P7 and P8. Table 5 from Section 4 showed the need to plant areas with varieties by the end of the season. Thus, as the planting areas have a higher productivity than the others, they provide a greater harvesting capacity for the resources, giving rise to this additional slack in the last macro-periods. By doing this, it reached the maximum level of milling, making the transportation resource restrictive. Although the transportation potential from the planting areas is below average, the difference is not significant (less than one ton per hour per vehicle).

Graph 6 shows the geographical distribution of the fronts and Graph 7 shows the sequencing of front 1, for example.



Graph 6. Geographical distribution of harvest blocks per front.



Graph 7. Sequencing of front 1.

It is clear by observing the graphs that in order for the plan to enable the balance between the harvesting and transportation capacities, a harvesting front can visit the same block several times at different times. A block can also be visited by several fronts, provided that the minimum amount to be harvested is respected during both visits. Therefore, this concept of sequencing harvesting fronts is quite different from the view of sectorization, a predominant in plants where blocks are previously assigned to harvesting fronts. It is important to point out that in cases where there are constraints concerning the transportation of workers from the harvesting fronts, the model can incorporate that. In fact, sectorization is a practice that could lead to good solutions if only the minimum stretch of the fronts was taken into account, without considering the balance between harvesting and transportation capacities.

It should be emphasized that not sectorizing, from the decision maker's point of view, can make the planning process chaotic if he/she does not have a tool available such as the one proposed in this study. Moreover, there are difficulties inherent to solving the programming problem for the whole harvest season, which is the focus of this research.

In conclusion, the solution obtained from Experiment 4, applied to sample A1 studied and using the model, demonstrates good quality for programming the harvesting fronts with the assumptions adopted in Section 4. Although a solution with *Gap*=0 was not obtained, i.e., proved to be optimal, there was no loss of milling and the amount of raw material of sugarcane left unharvested can be considered irrelevant. The data show the importance of using the harvesting, milling and transportation capacities, which includes the time spent on the front when moving area, as proposed by this study. Although sectorization provides support to the decision maker to obtain solutions without using tools, as the one proposed in this paper, in the case study of this company, it is not necessary to obtain a good solution.

6 Final considerations

The problem of programming harvesting fronts when aiming to balance the harvesting and transportation capacities is complex and challenging. The model 1B proposed by Junqueira & Morabito (2017) addresses this complexity relating variables that are not typically addressed in the literature, such as defining harvesting fronts as a response to the model, as well as the balance between harvesting and transportation capacities dependent on the harvesting blocks. The previous study showed great potential of economic gains in a small sized sample.

In this study, aggregation methods, as well as successful MIP-based heuristics in the literature such as relax-and-fix and fix-and-optimize were implemented to solve the problem of the large scale company studied. Various combinations of the heuristic methods proposed in this work, as well as different parameterizations of the CPLEX were tested and were able to obtain good solutions for the real problem. It should be pointed out that apart from the fact that the size of the problem was challenging, the slack capacity was quite tight, mainly regarding the harvest. Nevertheless solutions with acceptable computational times for planning the harvest could be obtained. It is worth mentioning that for the application of this type of approach in practice, a careful survey of the data is essential, including the analysis of each harvesting block in terms of harvesting and transport capacity, as well as the definition of the LTIU of the blocks considering the prevailing agronomic factors for the agricultural team of the plant.

Based on these studies, at least three perspectives for future research are relevant. The first one would be concerned with the development of heuristic methods for solutions using models 1 and 1A, proposed by Junqueira & Morabito (2017). A second line of research would be to apply this model to other plants with different characteristics from the one studied here in terms of distributing harvesting blocks and harvesting and transportation potential. Finally, the third line would be to use the solution obtained by Model 1B to guide planting and harvesting decisions, analyzing and comparing the results obtained from this approach with those from the previous approach.

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