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**Research Report**

## Tactical planning of sugarcane harvest and transport operations

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# Tactical planning of sugarcane harvest and transport operations

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## Abstract

Motivated by a real situation arising in the Brazilian sugarcane industry, this paper addresses the integrated planning of harvest and transport operations over a multi-period planning horizon. The aim is to develop a schedule for the deployment of harvest and transport equipment that specifies the periods for the execution of the harvest operations on the sugarcane fields, and the type of harvesting machines and transport vehicles to be operated. These decisions are made subject to multiple constraints related to the projected crop yield, resource availability, demand for sugarcane at the mills, and further technical requirements specific to the harvest operations. The tactical plan to be determined minimizes the total cost incurred by the equipment used and the total time required to harvest all the fields. We propose a bi-objective mixed-integer non-linear programming model for this new problem. A computational study is conducted for test instances capturing the characteristics of a Brazilian milling company. Pareto-optimal solutions are identified by the Progressive Bounded Constraint Method that is extended to the problem at hand. A comparative analysis highlights the trade-offs between economic performance and harvest efficiency, thereby supporting the decision maker in making a more informed choice of the preferred tactical plan. Useful managerial insights are also provided into the profile of the harvest and transport resources that should be used under different weather conditions and work schedules.

**Keywords:** Multi-objective optimization; Mixed-integer Programming; Sugarcane harvest and transport planning

## 1 Introduction

Brazil's sugarcane industry is one of the largest in the world and a key sector in the Brazilian economy. It supports around 1 million direct jobs, generates an annual revenue of US\$ 70 billion

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(Glueck (2015)), and contributes approximately 2 percent to Brazil's gross domestic product (UNICA (2017)). In the 2018/19 harvest season, Brazil ranked second after India, with a share of 16.5 percent (or 29.5 million tonnes) of the world's sugar production of 178.612 million tonnes (International Sugar Organization (2020); Statista (2020)). Brazil is expected to regain its position as the world's leading producer and exporter of sugar due to recent adverse weather conditions for sugarcane cultivation in Asian countries, especially India and Thailand, which will lead to a production decline in this region (Conab (2020)). In addition to the production of raw sugar, sugarcane can also be processed into ethanol to be used as a suitable alternative to fossil fuels. Brazil has the largest fleet of flexible-fuel vehicles in the world, which can run on either pure ethanol or on a mix of ethanol with gasoline (Antunes et al. (2019)). Furthermore, 82 percent of the biomass used in Brazil to generate electricity is derived from sugarcane residues (UNICA et al. (2019)).

Until recently, growing domestic demand for ethanol fuel in Brazil had resulted in the diversion of 65 percent of sugarcane towards ethanol production, with an estimated production of 34.45 billion liters in 2019 (Barros (2019, 2020)). However, the coronavirus COVID-19 pandemic and the resulting sharp decline in oil prices due to an unprecedented fall in demand are expected to negatively affect the ethanol industry, thereby significantly increasing the sugar production (Barros (2020)).

South-Central Brazil is the heart of the country's sugarcane industry, especially the state of São Paulo, which accounts for 90 percent of the total production, while the north-east region contributes the remaining 10 percent (Barros (2020)). The sugarcane production chain involves cane growing, cane harvesting, cane transport to the mills, and cane processing at the mills. Motivated by a real situation faced by a milling company operating in the state of São Paulo, we address in this paper a problem arising at the tactical level, which involves the combined planning of harvest and transport operations for sugarcane. Specifically, the problem consists in allocating available resources (i.e., harvesting machinery and transport vehicles) over a multi-period planning horizon. In addition, the execution of harvest operations in the fields and the trips to be performed by vehicles to deliver sugarcane to the processing facilities also need to be scheduled. These decisions are affected by several factors, such as the projected crop yield and the estimated maturity period of the cane in each individual field, the characteristics and availability of machinery and vehicles, the expected demands of the mills, and further technical issues associated with harvesting. We propose a mixed-integer non-linear programming (MINLP) model for this tactical planning problem. Two objectives are

considered, namely the minimization of the total cost incurred by the harvesting machinery and the road haulage vehicles used, and the minimization of the total time needed to harvest a set of geographically dispersed sugarcane fields. The most effective way of reducing the harvest time is to increase machinery efficiency and fleet size, which usually comes at the expense of higher operating costs. Thus, the two objectives are conflicting.

Depending on the country, harvest operations may account for more than 30 percent of the total sugarcane production cost (Salassi and Barker (2008)). Transportation also represents an important cost component of the logistics planning with a share of more than one-third of the total cost (Martin et al. (2001); Masoud et al. (2016b); Saranwong and Likasiri (2016)). Therefore, reducing costs in harvesting and transport of sugarcane is a significant business driver. Cost savings can be achieved through integrated planning of both harvest and transport operations. In general, a lack of coordination among the decision makers involved in these activities affects the efficiency of the whole system. The potential benefit of the novel model that we propose in this paper is to assist decision makers at the tactical planning level in improving the overall performance of their harvest and transport operations through better resource allocation.

The contributions of the present work are summarized as follows: (1) We develop a bi-objective MINLP formulation for simultaneously planning harvest and transport decisions at a milling company managing multiple sugarcane fields and processing facilities. As our review of the literature will show, significant differences among sugar-producing countries substantiate the need to create a new model that addresses the specific organizational context of the Brazilian sugarcane industry at the tactical planning level. (2) We apply different linearization techniques to obtain a computationally tractable formulation. (3) We extend the Progressive Bounded Constraint method to identify Pareto-optimal solutions for the problem at hand. (4) We evaluate the results of a computational study on a set of semi-randomly generated instances that capture the characteristics of a Brazilian milling company. In particular, we provide important managerial insights that reveal the trade-offs between economic performance and harvest efficiency, and assist the decision maker in making an informed choice of the preferred tactical plan.

The remainder of this paper is organized as follows. Section 2 gives an overview of the relevant literature. In Section 3, we formally describe our problem and present a bi-objective MINLP formulation. Linearization techniques are also introduced that yield an equivalent model. In Section 4, the solution methodology is described. Computational results are reported in Section 5. Section 6 presents a summary of our findings and directions for future research.

## 2 Literature review

In this section, we review selected research articles related to decision making in the sugarcane industry. Our aim is not to provide an exhaustive review of this field but to analyze the extent to which the features captured by our model have been addressed in the literature. Accordingly, special emphasis will be given to works dealing with the optimization of harvest and transport operations, either individually or together.

The sugarcane production chain has been widely studied in the literature and many optimization models have been proposed over the years. Particular attention has been given to harvest scheduling problems since harvesting is at the core of the production chain, as for any other agricultural product (Ahumada and Villalobos (2009); Kusumastuti et al. (2016)). Such problems involve the allocation of the available resources (e.g., harvesting machinery, workforce) and the specification of an execution plan for the harvest operations over a planning horizon, taking into account a number of technical issues regarding the way the operations should be conducted. The latter are affected by the practices in place, which significantly differ across sugar-producing countries (Dourigel et al. (2018); Lamsal et al. (2017)). Jena and Poggi (2013) propose a hierarchical scheme in which at the tactical level, a mixed-integer linear programming (MILP) model is used to decide in which fields sugarcane should be harvested on each week of the harvest season in order to maximize total profit. Given the resulting optimal schedule, daily activities are planned at the operational level by means of a second MILP formulation. Junqueira and Morabito (2019) present a MILP model that simultaneously addresses tactical and operational harvest decisions. Since the model is computationally intractable for real-sized instances, a two-phase heuristic algorithm is developed. Other studies focus on either tactical harvest planning problems (Jiao et al. (2005); Thuankaewsing et al. (2015)) or problems at the operational level, where the planning horizon is divided into a given number of days or even shorter time periods (Higgins (2002); Kong et al. (2019); Stray et al. (2012)). In the aforementioned works, and in addition to various constraints specific to the particular problem and country, resource planning mainly involves workforce (e.g., crews that operate machinery, support the infield operations, or are engaged in manual cutting of the sugarcane). The choice of different types of mechanical harvesters is not included in the set of decisions, which is a feature that is explicitly considered in the model to be presented in Section 3. Since mechanization of sugarcane harvesting has been actively promoted in Brazil through environmental public policies (Conab (2020)), it is meaningful to account for this issue. Moreover, mechanical

harvesting improves sugarcane productivity and thus contributes to increasing competitiveness in the market.

Managing transport operations within the sugarcane fields or between the fields and the mills has also received some attention in the literature. At the operational level, route planning is studied by Kittilertpaisan and Pathumnakul (2017), Pitakaso and Sethanan (2019), Santoro et al. (2017), and Sethanan and Neungmatcha (2016). Generally, routes are designed for harvesting machines in order to minimize the total operating time or total operating cost, while satisfying a given set of service requirements (e.g., time windows reflecting individual field working conditions and cane maturity levels). In Australia, sugarcane freight transport is predominantly handled by mill-owned rail systems. Trains deliver empty bins from the mills to the farms and collect full bins from the farms to return to the mills for processing. Mixed-integer linear programming and constraint programming have been applied to schedule rail transports to a mill over a 24 hour period subject to a number of constraints that are specific to the Australian rail system (Martin et al. (2001); Masoud et al. (2015, 2016a,b)). In Cuba, sugarcane can be transported either directly from the field to the mill using road transport or via intermediate storage facilities. In the latter case, intermodal transportation is employed, combining road transport to the storage facility and rail transport thereafter. López-Milán and Plà-Aragónés (2014) propose a decision support system for planning daily cane transports in Cuba which uses a MILP model developed by López-Milán et al. (2006). Higgins (2006) applies tabu search and variable neighborhood search heuristics to determine a detailed daily schedule for road transport vehicles that pick up full trailers of cane from the farms and deliver them to the mill. Our work differs from the aforementioned studies in that we address the tactical level, instead of the operational level, and plan road transports of sugarcane to multiple processing facilities, instead of a single mill, using a heterogeneous vehicle fleet. Iannoni and Morabito (2006) evaluate different dispatching strategies by means of discrete event simulation that involve distinct types of vehicles serving three mills. Focus is given to improving the operations in the reception area of the mills (e.g., weighing and unloading of the trucks, assessment of the quality of the cane). The allocation of the vehicles to the fields and the creation of vehicle schedules are not modeled.

Several authors have highlighted the importance of integrated planning of multiple agricultural operations (Ahumada and Villalobos (2009); Kusumastuti et al. (2016)). A few contributions address the simultaneous generation of cultivation and harvest plans, taking into account the specific characteristics of different sugarcane varieties, which in turn affect the decision



in which periods harvest operations should be performed and in which fields (Carvajal et al. (2019); Florentino et al. (2020); Higgins (1999)). Concerning the combined planning of harvest and transport activities, early studies apply discrete event simulation to evaluate the impact of varying the resource availability (i.e., workforce, harvest equipment, transport vehicles) to supply a single processing facility. Arjona et al. (2001) simulate the harvest and transport operations over the course of one day, and consider intermodal transports involving trucks and ferries. For a time horizon of one week divided into hour intervals, the model developed by Hansen et al. (2002) simulates manual harvest operations and the transport of the cane to a mill using farm-owned or sub-contracted vehicles. Grunow et al. (2007) propose a hierarchical scheme that comprises cultivation planning, harvest scheduling, and crew and equipment dispatching. At the tactical level, the timing for harvesting is set along with the choice of the harvest mode (manual or mechanical) and the transport volume to be delivered to a mill by means of a MILP model that minimizes total cost. The tactical plan is used to create detailed crew and equipment dispatch schedules at the operational level. Salassi and Barker (2008) present a MILP formulation to determine an optimal harvest and transport schedule for a group of farms delivering sugarcane to a common mill with the goal of minimizing the waiting time of the trucks upon their arrival at the mill. A homogenous vehicle fleet and a homogeneous set of harvesters are assumed to be available. Silva et al. (2015) propose a multi-choice goal programming model to determine the timing and the varieties of sugarcane that should be harvested manually or with mechanical harvesters, and transported to a mill over the harvest season. Two modes of transportation are offered, namely mill-owned vehicles and third-party vehicles. The MILP model developed by Morales-Chávez et al. (2016) allocates machines and workers to fields and transport volumes to a biofuel plant at the tactical level, considering one single period. The total cost to be minimized includes machinery, workforce, and transport costs as well as penalty costs for unsatisfied demand. Lamsal et al. (2016a) present a two-phase solution approach, in which the first phase consists of fixing the harvest start times at a set of geographically dispersed fields over several time intervals spanning one day. The objective is to minimize the total deviation between the quantity of sugarcane that is transported to the mill and the mill's demand in each time interval. The optimal solution obtained to the associated MILP model is used in the second phase to determine the number of trucks needed to transport the cane to the mill by the arrival times prescribed in the first phase. The authors also address the problem from a continuous time perspective by considering infinitesimal time blocks (Lamsal et al. (2016b)). For the discrete-time model, Lamsal et al. (2017) introduce

valid inequalities and heuristics to find an initial feasible solution and to lift the lower bound provided by the linear relaxation. Even though a few authors have dealt with integrated harvest and transport planning as shown by our review, focus has been primarily given to operational problems in which each harvest location is assigned to a specific processing facility in advance. Hence, allocation decisions involving multiple sugarcane fields and multiple mills are not explicitly addressed by any model. Moreover, decisions on the type of harvest equipment and transport vehicles to be used are also not incorporated into the proposed optimization models. By contrast, these features are captured by our model at the tactical planning level.

Given the numerous stakeholders and their individual interests, planning problems with conflicting objectives occur frequently along the sugarcane production chain. Yet, the majority of the mathematical programming models reviewed before have a single objective. An approach followed by some authors (e.g., Higgins (2002)) is to convert multiple decision criteria into a single-objective scalar function by assigning weights to the individual criteria. Florentino et al. (2011, 2018), Florentino and Pato (2014), Kittilertpaisan and Pathumnakul (2017), Masoud et al. (2016a), Sethanan and Neungmatcha (2016), and Silva et al. (2015) are among the few authors that formulate their optimization models with multiple (mainly two) objectives. Different techniques have been applied to solve these problems, namely the  $\varepsilon$ -constraint method, goal programming, and various heuristic methods. The problem that we address in this paper is formulated with two conflicting objectives, in which one of them is described by a non-linear function. In addition, since some technical issues specific to the Brazilian sugarcane industry are modeled by non-linear constraints, these features result in a challenging non-convex problem (cf. Section 3).

Table 1 summarizes the main characteristics of the works reviewed in this section and that are related to the problem that we study. Our classification scheme has five categories. The category 'Planning scope' (columns 2–4) comprises the strategic, tactical, and operational levels according to the planning horizon. The category 'Decision planning' (columns 5–8) includes the main types of planning problems related to harvest and transport operations. The category 'Modeling approach' (column 9) considers simulation and optimization models, and specifies the features of the latter. The category 'Objective function' (columns 10–11) indicates if a single objective or multiple objectives are considered. The last category classifies the solution approach adopted by the researchers. We distinguish between those problems solved to optimality (column 12) and those solved with a specially tailored heuristic algorithm (column 13). The majority of the problems are optimally solved with general-purpose optimization software under

default parameter settings. Some researchers also develop valid inequalities and other enhancements to improve the tractability of their models (e.g., Jena and Poggi (2013); Lamsal et al. (2016b, 2017)). The last row in Table 1 highlights the main features that are captured by our model and that will be detailed in the next section.

### 3 Problem statement and formulation

We consider a milling company that operates a number of large mills where sugarcane is processed to produce sugar and ethanol. The biomass residue (bagasse) that is left, after the sugarcane is crushed, is used as fuel source by the mills to cover their needs for heat and electrical energy (Florentino and Pato (2014)). Sales forecasts set the production levels at the mills, which in turn determine their demand levels for sugarcane in each time period.

The company also manages a set of geographically dispersed fields in the state of São Paulo (Brazil), whose individual areas range from 25 to 100 hectares. Farmers rent out their lands for a specified period of time (e.g., 5 years), during which the company is responsible for all operations involving sowing, growing, harvesting, and supplying the mills with sugarcane. Over the harvest season and for each field, an individual time window is specified for harvesting which depends on the projected maturation of the sugarcane and weather forecasts.

Brazilian regulations on sugarcane harvesting have resulted in a significant increase in the use of machinery over the years, particularly in the south-central region. Harvest equipment is owned or hired by the milling company, and depending on the cutting capacity and other technical characteristics, a mechanical harvester can harvest 10-30 tonnes of cane per hour. Typically, the equipment is stored in a depot whose location may be adjacent to one of the mills or in a convenient site in the milling area. Due to the high cost of the machinery, which comprises depreciation, energy, maintenance, repair, labor, and transport costs, once a harvester starts working in a field, it remains in that field until all sugarcane is harvested, even if this operation may take several periods. Moreover, minimum and maximum time limits for operating a harvesting machine at a period are imposed, depending on the type of equipment and the labor contracts negotiated. Unlike other countries (e.g., Australia and Cuba), sugarcane harvesting in Brazil is not limited to daylight hours, and up to three 8-hour shifts can be run each day, also on weekends.

After the cane is harvested, it is transported directly to the mills to be processed. In Brazil,

Reference	Planning scope					Decision planning					Modeling approach		Objective function		Solution approach	
	S	T	O	H	R	TR	H+TR	approach	Single	Multiple	Exact	Heuristic				
Arjona et al. (2001)			*				*	DES			*					
Florentino et al. (2011)	*					*		BILP		*	*	*				
Florentino and Pato (2014)	*					*		BILP		*	*	*				
Florentino et al. (2018)		*		*				GP		*	*	*				
Grunow et al. (2007)		*	*				*	MILP			*					
Hansen et al. (2002)		*	*	*			*	DES	*		*					
Higgins (2002)		*	*	*			*	INLP	*		*	*				
Higgins (2006)		*	*	*			*	MILP	*		*	*				
Iannoni and Morabito (2006)		*	*	*			*	DES	*		*	*				
Jena and Poggi (2013)		*	*	*			*	MILP	*		*	*				
Jiao et al. (2005)		*	*	*			*	LP	*		*	*				
Junqueira and Morabito (2019)		*	*	*			*	MILP	*		*	*				
Kittilertpaisan and Pathumnakul (2017)		*	*	*	*		*	MILP	*	*	*	*				
Kong et al. (2019)		*	*	*			*	MILP	*		*	*				
Lamsal et al. (2016a, 2017)		*	*	*			*	MILP	*		*	*				
Lamsal et al. (2016b)		*	*	*			*	ILP	*		*	*				
López-Milán et al. (2006)		*	*	*		*	*	MILP	*		*	*				
López-Milán and Plà-Aragónés (2014)		*	*	*		*	*	MILP	*		*	*				
Martin et al. (2001)		*	*	*		*	*	MILP	*		*	*				
Masoud et al. (2015)		*	*	*		*	*	MILP	*		*	*				
Masoud et al. (2016a)		*	*	*		*	*	MILP	*	*	*	*				
Masoud et al. (2016b)		*	*	*		*	*	MILP, CP	*	*	*	*				
Morales-Chávez et al. (2016)		*	*	*		*	*	MILP	*	*	*	*				
Pitakaso and Sethanan (2019)		*	*	*	*		*	MILP	*	*	*	*				
Salassi and Barker (2008)		*	*	*		*	*	BILP	*	*	*	*				
Santoro et al. (2017)		*	*	*		*	*	MILP	*	*	*	*				
Sethanan and Neungmatcha (2016)		*	*	*		*	*	GP	*	*	*	*				
Silva et al. (2015)		*	*	*		*	*	ILP	*	*	*	*				
Stray et al. (2012)		*	*	*		*	*	MILP	*	*	*	*				
Thuankaeuwssing et al. (2015)		*	*	*		*	*	MILP	*	*	*	*				
<b>New model (cf. Section 3)</b>		*	*	*		*	*	<b>MINLP</b>	*	*	*	*				

S: Strategic; T: Tactical; O: Operational; H: Harvest planning/scheduling; R: Routing; TR: Transport; H+TR: Harvest and transport; BILP: Binary integer linear programming; CP: Constraint programming; DES: Discrete event simulation; GP: Goal programming; ILP: Integer linear programming; INLP: Integer non-linear programming; LP: Linear programming; MILP: Mixed-integer linear programming; MINLP: Mixed-integer non-linear programming

Table 1: Main features of literature dedicated to planning sugarcane harvest and transport operations.

transport of sugarcane is mostly performed by road haulage vehicles. In our case, transport equipment is owned by the milling company, although occasionally additional vehicles may be hired from third-party logistics partners to cover peak harvest periods. Since the quantity cut by a harvester over a time period often exceeds the capacity of a single vehicle, more than one collection and delivery per field and per period are necessary. Hence, vehicles commute between the fields and the mills. The time for full loading a vehicle at a harvest location and the time for unloading it at the processing facility are assumed to be known. The time dedicated to these tasks is called *service time* hereafter. The available vehicles differ in transport capacity, speed, and operating cost. Coordination of the harvest and transport operations requires the vehicles' work shifts to coincide with the operating times of the harvest equipment.

The mathematical model to be presented in Sections 3.1–3.2 supports the integrated planning of harvest and transport operations over a time horizon that can span either the entire harvest season (i.e., from April to December) or a pre-selected part of it. The planning horizon is divided into a finite number of (usually equal-length) time periods. The aim is to determine the timing and duration of harvest operations in each field, the choice of equipment (i.e., harvesters and transport vehicles) from the available alternatives, and the timing and number of commuting trips to be made by the different vehicles. These tactical decisions must meet a given set of constraints that include the achievement of the productivity targets set for the fields, the satisfaction of the demands of the mills, the execution of harvest activities within the time windows specified for the individual fields, the utilization of equipment according to its availability and capacity, and the satisfaction of further technical requirements specific to the harvest conditions in place at the milling company. A trade-off is to be considered between minimizing the total cost incurred by the harvest and transport operations and minimizing the total harvest time. Accordingly, two objective functions are formulated that are conflicting owing to the fact that a reduction of the harvest time can only be achieved either by increasing the use of equipment or by using more efficient but at the same time more expensive equipment.

Before detailing the optimization model for the problem described, we first introduce the notation that will be used hereafter.

### 3.1 Notation

We start by defining the sets used in our model.

$I$	Set of fields to be harvested.
$J$	Set of sugar mills.
$K$	Set of different types of cane transport vehicles.
$L$	Set of different types of harvesting machines.
$T$	Set of time periods along the planning horizon.
$HT_i$	Subset of time periods during which field $i \in I$ can be harvested; $HT_i = \{a_i, a_i + 1, \dots, b_i - 1, b_i\}$ , with $a_i$ ( $b_i$ ) denoting the earliest (latest) time period harvesting can begin (be completed) in field $i$ .
$I_t$	Subset of fields that can be harvested in time period $t \in T$ ; $I_t = \{i \in I : t \in HT_i\} \subseteq I$ .

The following parameters are defined for fields and sugar mills.

$A_i$	Area of field $i \in I$ (in ha).
$P_i$	Productivity of field $i \in I$ (in tonnes/ha).
$d_{jt}$	Demand for sugarcane (in tonnes) at mill $j \in J$ in time period $t \in T$ .
$\delta$	A sufficiently small, positive number.

For cane transport vehicles, the following parameters are introduced:

$V_{kt}^{max}$	Number of vehicles of type $k \in K$ available at time period $t \in T$ .
$C_k^{max}$	Maximum capacity (in tonnes) of a vehicle of type $k \in K$ .
$s_k^e, s_k^f$	Average empty, resp. loaded, travel speed (in km/h) of a vehicle of type $k \in K$ .
$st_k$	Service time (in hours) of a vehicle of type $k \in K$ . It includes the amount of time required to load a vehicle in a field and unload it at a mill.
$hw_t^{max}$	Maximum transport time (in hours) of a vehicle in time period $t \in T$ .
$D_{ij}$	Travel distance (in km) between field $i \in I$ and mill $j \in J$ .
$D_i^0$	Travel distance (in km) between the depot where harvesting machines are kept and field $i \in I$ .
$n_{ijkt}$	Proportion of period $t \in HT_i$ required by a round trip of a vehicle of type $k \in K$ between field $i \in I$ and mill $j \in J$ .

Following a similar approach to the one adopted by López-Milán and Plà-Aragonés (2014), the last parameter takes into account the distance traveled by a vehicle, the service time of a vehicle, and its round trip travel time. The latter includes an empty journey from the mill to

the field and a return journey with a full load. Hence,  $n_{ijkt}$  is defined as:

$$n_{ijkt} = \frac{D_{ij} \left( (s_k^e)^{-1} + (s_k^f)^{-1} \right) + st_k}{hv_t^{max}} \quad i \in I, j \in J, k \in K, t \in HT_i.$$

Regarding the harvesting machines, the following parameters are introduced:

- $M_{\ell t}^{max}$  Number of harvesting machines of type  $\ell \in L$  available at time period  $t \in T$ .
- $Q_{\ell}$  Quantity of sugarcane (in tonnes/h) that can be harvested by a machine of type  $\ell \in L$ .
- $h_t^{min}, h_t^{max}$  Minimum and maximum operating time (in h) of a harvesting machine in time period  $t \in T$ .

Finally, cost parameters are expressed in monetary units (m.u.) and defined as follows:

- $p_{kt}$  Transport cost (in m.u./km) of a vehicle of type  $k \in K$  in time period  $t \in T$ .
- $hd_t$  Driver's wage rate (in m.u./h) in time period  $t \in T$ .
- $mc_{\ell t}$  Cost (in m.u./h) of operating a machine of type  $\ell \in L$  in time period  $t \in T$ .
- $hm_t$  Machine operator's wage rate (in m.u./h) in time period  $t \in T$ .
- $p_t^0$  Cost (in m.u./km) of moving a harvesting machine between the depot and a sugarcane field in time period  $t \in T$ .
- $c_{ijkt}^1$  Total transport cost (in m.u.) of a round trip traveled by a vehicle of type  $k \in K$  between field  $i \in I$  and mill  $j \in J$  in time period  $t \in HT_i$ , with

$$c_{ijkt}^1 = 2 p_{kt} D_{ij} + hd_t \left[ D_{ij} \left( (s_k^e)^{-1} + (s_k^f)^{-1} \right) + st_k \right].$$

- $c_{\ell t}^2$  Total operating cost (in m.u./h) of a harvesting machine of type  $\ell \in L$  in time period  $t \in T$ , with  $c_{\ell t}^2 = mc_{\ell t} + hm_t$ .
- $c_{it}^3$  Total cost (in m.u.) of moving a harvesting machine from the depot to field  $i \in I$  in time period  $t \in T$ , and returning the machine when the harvest activity is finished, with  $c_{it}^3 = 2 p_t^0 D_i^0$ .

Observe that transport costs are incurred on vehicle round trips and not on the volume

of cargo carried by the vehicles since they always travel with full-loads to the mills and return empty to the fields. Specifically, travel costs and driver's wages set the values of parameters  $c_{ijkt}^1$ . Moreover, machine operating costs ( $c_{\ell t}^2$ ) are not affected by the quantity harvested but on the number of hours worked. Harvesters are transported by special vehicles to the fields and returned to the depot for cleaning, inspection and maintenance, before they are assigned to new tasks. We assume that the cost of transporting a machine is twice the cost of an outward journey, regardless of the period at which the return journey takes place (cf.  $c_{it}^3$ ).

### 3.2 Bi-objective mixed-integer non-linear programming formulation

The bi-objective MINLP formulation to be presented next uses binary variables to represent the assignment of harvest operations to fields, integer variables associated with the number of harvesting machines used and the number of round trips performed by the different vehicles, and continuous variables for measuring the time dedicated to harvesting.

$$s_{it} = \begin{cases} 1 & \text{if field } i \in I \text{ is harvested in time period } t \in T \\ 0 & \text{otherwise.} \end{cases}$$

$x_{ijk t}$  : number of round trips traveled by a vehicle of type  $k \in K$  between field  $i \in I$  and mill  $j \in J$  in time period  $t \in HT_i$ .

$z_{i\ell t}$  : number of harvesting machines of type  $\ell \in L$  assigned to field  $i \in I$  in time period  $t \in HT_i$ .

$h_{it}$  : number of hours dedicated to harvesting field  $i \in I$  in time period  $t \in HT_i$ .

In addition, the following slack variables are introduced:

$e_{it}$  : total surplus quantity of sugarcane (in tonnes) transported from field  $i \in I$  to the mills in time period  $t \in T$ .

The bi-objective MINLP formulation is as follows:

$$\text{Min } w_1 = \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in HT_i} c_{ijk t}^1 x_{ijk t} + \sum_{i \in I} \sum_{\ell \in L} \sum_{t \in HT_i} c_{\ell t}^2 h_{it} z_{i\ell t} + \sum_{i \in I} \sum_{\ell \in L} c_{i,a_i}^3 z_{i,\ell,a_i} +$$



$$\sum_{i \in I} \sum_{\ell \in L} \sum_{t \in HT_i \setminus \{b_i\}} c_{i,t+1}^3 (z_{i,\ell,t+1} - z_{ilt}) s_{i,t+1} \quad (1)$$

$$\text{Min } w_2 = \sum_{i \in I} \sum_{t \in HT_i} h_{it} \quad (2)$$

subject to

$$\sum_{\ell \in L} \sum_{t \in HT_i} Q_\ell h_{it} z_{ilt} = A_i P_i \quad i \in I \quad (3)$$

$$\sum_{j \in J} \sum_{k \in K} C_k^{max} x_{ijkt} - e_{it} = \sum_{\ell \in L} Q_\ell h_{it} z_{ilt} \quad i \in I, t \in HT_i \quad (4)$$

$$\sum_{i \in I_t} \sum_{k \in K} C_k^{max} x_{ijkt} \geq d_{jt} \quad j \in J, t \in T \quad (5)$$

$$\sum_{i \in I_t} \sum_{j \in J} [n_{ijkt} x_{ijkt}] \leq V_{kt}^{max} \quad k \in K, t \in T \quad (6)$$

$$\sum_{i \in I_t} z_{ilt} \leq M_{lt}^{max} \quad \ell \in L, t \in T \quad (7)$$

$$[n_{ijkt} x_{ijkt}] + z_{ilt} \leq (V_{kt}^{max} + M_{lt}^{max}) s_{it} \quad i \in I, j \in J, k \in K, \quad \ell \in L, t \in HT_i \quad (8)$$

$$\sum_{j \in J} \sum_{k \in K} [n_{ijkt} x_{ijkt}] \geq s_{it} \quad i \in I, t \in HT_i \quad (9)$$

$$\sum_{\ell \in L} z_{ilt} \geq s_{it} \quad i \in I, t \in HT_i \quad (10)$$

$$h_t^{min} s_{it} \leq h_{it} \leq h_t^{max} s_{it} \quad i \in I, t \in HT_i \quad (11)$$

$$s_{it} + s_{i,t+n+1} - 1 \leq \frac{1}{n} \sum_{j=1}^n s_{i,t+j} \quad i \in I, n \in \{1, \dots, b_i - a_i - 1\}, \quad t \in HT_i \setminus \{b_i - n, \dots, b_i\} \quad (12)$$

$$z_{ilt} \leq z_{i,\ell,t+1} + M_{lt}^{max} (1 - s_{i,t+1}) \quad i \in I, \ell \in L, \quad t \in HT_i \setminus \{b_i\} \quad (13)$$

$$s_{it} \in \{0, 1\} \quad i \in I, t \in HT_i \quad (14)$$

$$x_{ijkt} \geq 0 \text{ and integer} \quad i \in I, j \in J, k \in K, \quad t \in HT_i \quad (15)$$

$$z_{ilt} \geq 0 \text{ and integer} \quad i \in I, \ell \in L, t \in HT_i \quad (16)$$

$$h_{it} \geq 0 \quad i \in I, t \in HT_i \quad (17)$$

$$0 \leq e_{it} \leq \min_{k \in K} \{C_k^{max}\} - \delta \quad i \in I, t \in HT_i \quad (18)$$

The first objective function (1) minimizes the total estimated cost of harvesting the sugarcane and transporting it to the mills. Specifically, the first component represents the total cost incurred by the round trips made by the vehicles, while the second component accounts for the total cost for operating harvesting machines. The last two components are associated with the cost of moving harvesters between the depot and the fields. We note that for practical reasons, the number of harvesters operating in a particular field is non-decreasing over consecutive harvesting periods (cf. constraints (13)). Hence, the term  $(z_{i,\ell,t+1} - z_{i\ell t})$  in the last component of (1) is non-negative. The second objective function (2) aims at minimizing the total harvest time.

Constraints (3) ensure that all sugarcane grown in a field is harvested over the associated harvest time window. Constraints (4) guarantee that the total amount of sugarcane transported from a field to the mills in a given time period is not less than the quantity harvested. Since it is assumed that vehicles always travel with a full-load on their journeys to the mills, the total quantity transported from a field may exceed the actual quantity of sugarcane grown in that field. The slack variables  $e_{it}$  account for this difference, and as it will be explained below, a meaningful upper bound on the values they can take is imposed (cf. constraints (18)). This type of approach for resource allocation at the tactical planning level has also been adopted in other contexts, e.g., Schilling and Georgiadis (2002) and Westerlund et al. (1998) for a one-dimensional cutting stock problem.

The demands of the mills must be satisfied according to constraints (5). In each time period, the total number of used cane transport vehicles of a given type is limited by inequalities (6). Similar conditions are enforced by inequalities (7) on the number of operating harvesters. Constraints (8) ensure that vehicles and harvesters are not assigned to a field in a given period unless harvest operations take place in that field. According to constraints (9) and (10), at least one vehicle and at least one machine must be used when a field is harvested. Inequalities (11) set lower and upper limits on the time dedicated to harvest operations in a field over each period. For practical reasons, constraints (12) require consecutive time periods to be selected for harvesting a field. If harvest operations take place in field  $i$  in time periods  $t$  and  $t + n + 1$  (i.e.,  $s_{it} = s_{i,t+n+1} = 1$  for  $n \geq 1$ ) then these constraints make sure that all intermediate periods  $t + 1, \dots, t + n$  also have harvest operations (i.e.,  $s_{i,t+1} = \dots = s_{i,t+n} = 1$ ). Figure 1 illustrates these conditions. Also for practical reasons, constraints (13) state that a non-decreasing number of machines must be used in consecutive periods dedicated to harvest-

ing a field. Hence, if field  $i$  is harvested in periods  $t$  and  $t + 1$  (i.e.,  $s_{it} = s_{i,t+1} = 1$ ), it follows from (13) that the inequality  $z_{ilt} \leq z_{i,\ell,t+1}$  holds, and as a result, this requirement is satisfied. Finally, non-negativity, integrality, and binary conditions are given by (14)–(18).

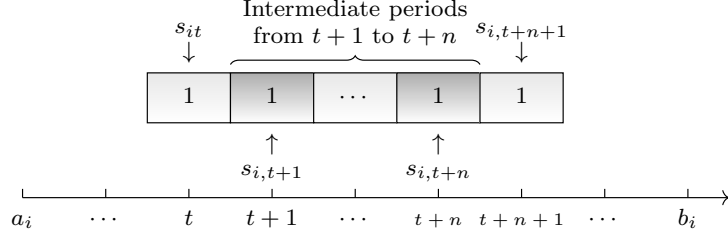


Figure 1: Consecutive periods dedicated to harvesting a field (cf. constraints (12)).

We illustrate the usefulness of bounding the slack variables  $e_{it}$  in (18) by means of an example. Let us consider two types of vehicles with capacities  $C_1^{max} = 60$  tonnes and  $C_2^{max} = 75$  tonnes, respectively. A sufficiently large number of vehicles of each type are assumed to be available. Moreover, let the total quantity of sugarcane harvested in field  $i$  be 650 tonnes ( $= \sum_{\ell \in L} Q_\ell h_{it} z_{ilt}$ ) in some period  $t$ . Under the assumption that a vehicle always travels with a full-load to a mill, there is no combination of vehicles whose total capacity is exactly 650 tonnes. The upper bound in (18) restricts the amount transported in excess to less than the capacity of the smallest vehicle available (i.e.,  $e_{it} < 60$ ). For this particular case, Table 2 lists all possible alternatives for organizing the transport of sugarcane. Columns 2 and 3 give the total number of vehicles of each type used. The last column indicates the value of  $e_{it}$  associated with each option, which is obtained according to (4). Further combinations of vehicles yield a too large excess load and are, therefore, inefficient. Hence, the upper bound set on the slack variables limits the number of feasible solutions without excluding any optimal solution.

Option	No. of vehicles of type 1 used	No. of vehicles of type 2 used	Total quantity transported	Excess sugarcane transported
1	0	9	675	25
2	1	8	660	10
3	11	0	660	10
4	10	1	675	25
5	9	2	690	40
6	8	3	705	55

Table 2: Example illustrating alternative choices for vehicles to transport sugarcane.

### 3.3 Linearization techniques and an equivalent formulation

The mathematical formulation (1)–(18) includes several non-linear terms, namely in the objective function (1) and in constraints (3), (4), (6), (8), and (9). In this section, we propose a reformulation as a bi-objective MILP model by using three linearization techniques.

To linearize the product of a non-negative integer variable with a binary variable that appears in the last component of the objective function (1), we define a new variable  $\gamma_{ilt}$  such that  $\gamma_{ilt} = (z_{i,\ell,t+1} - z_{ilt}) s_{i,t+1}$  for every  $i \in I$ ,  $\ell \in L$ , and  $t \in HT_i \setminus \{b_i\}$ . In addition, considering that the variables  $z_{ilt}$  are bounded by the number of available harvesting machines,  $M_{\ell t}^{max}$ , the variable substitution is described by the following linear constraints:

$$\gamma_{ilt} \leq M_{\ell t}^{max} s_{i,t+1} \quad i \in I, \ell \in L, t \in HT_i \setminus \{b_i\} \quad (19)$$

$$\gamma_{ilt} \leq z_{i,\ell,t+1} - z_{ilt} \quad i \in I, \ell \in L, t \in HT_i \setminus \{b_i\} \quad (20)$$

$$\gamma_{ilt} \geq z_{i,\ell,t+1} - z_{ilt} - M_{\ell t}^{max} (1 - s_{i,t+1}) \quad i \in I, \ell \in L, t \in HT_i \setminus \{b_i\} \quad (21)$$

Regarding the bilinear terms involving non-negative continuous variables and non-negative integer variables in constraints (3), (4), and in the second component of the objective function (1), we replace them by the new set of continuous variables  $y_{ilt}$  ( $i \in I$ ,  $\ell \in L$ ,  $t \in HT_i$ ). Furthermore, we model the binary expansion of the integer variables  $z_{ilt}$ , which involves defining a new set of binary variables,  $\alpha_{iltr}$ , and enforcing

$$z_{ilt} = \sum_{r \in R_{\ell t}} 2^{r-1} \alpha_{iltr} \quad i \in I, \ell \in L, t \in HT_i, \quad (22)$$

with  $R_{\ell t} = \{1, \dots, \lceil \log_2(M_{\ell t}^{max}) \rceil + 1\}$ . Hence, the bilinear terms in (1), (3), and (4) can be replaced by:

$$y_{ilt} = h_{it} z_{ilt} = h_{it} \sum_{r \in R_{\ell t}} 2^{r-1} \alpha_{iltr} = \sum_{r \in R_{\ell t}} 2^{r-1} (h_{it} \alpha_{iltr}) \quad i \in I, \ell \in L, t \in HT_i$$

We now introduce a new set of non-negative continuous variables  $\beta_{iltr} = h_{it} \alpha_{iltr}$  ( $i \in I$ ,  $\ell \in L$ ,  $t \in HT_i$ ,  $r \in R_{\ell t}$ ), and derive the following linear constraints:

$$y_{ilt} = \sum_{r \in R_{\ell t}} 2^{r-1} \beta_{iltr} \quad i \in I, \ell \in L, t \in HT_i \quad (23)$$

Considering that the continuous variables  $h_{it}$  are bounded by  $h_t^{max}$ , the linearization of the term  $h_{it} \alpha_{iltr}$  follows along the same lines as those presented in (19)–(21), namely

$$\beta_{iltr} \leq h_t^{max} \alpha_{iltr} \quad i \in I, \ell \in L, t \in HT_i, r \in R_{\ell t} \quad (24)$$

$$\beta_{iltr} \leq h_{it} \quad i \in I, \ell \in L, t \in HT_i, r \in R_{\ell t} \quad (25)$$

$$\beta_{iltr} \geq h_{it} - h_t^{max} (1 - \alpha_{iltr}) \quad i \in I, \ell \in L, t \in HT_i, r \in R_{\ell t} \quad (26)$$

The technique used to develop the constraints (22)–(26) along with  $y_{ilt} \geq 0$ ,  $\alpha_{iltr} \in \{0, 1\}$ , and  $\beta_{iltr} \geq 0$ , for every  $i \in I$ ,  $\ell \in L$ ,  $t \in HT_i$ , and  $r \in R_{\ell t}$ , yields an exact linearization of the original bilinear terms as shown by Gupte et al. (2013).

Finally, the ceiling function on the left-hand side of constraints (6), (8), and (9) is linearized by defining a new set of non-negative integer variables,  $x_{ijkt}^c$  ( $i \in I$ ,  $j \in J$ ,  $k \in K$ ,  $t \in HT_i$ ), that replace the term  $\lceil n_{ijkt} x_{ijkt} \rceil$ , and by adding the following constraints:

$$x_{ijkt}^c \geq n_{ijkt} x_{ijkt} \quad i \in I, j \in J, k \in K, t \in HT_i \quad (27)$$

$$x_{ijkt}^c \leq n_{ijkt} x_{ijkt} + (1 - \delta) \quad i \in I, j \in J, k \in K, t \in HT_i \quad (28)$$

The reformulation of the MINLP model defined by (1)–(18) into an equivalent MILP model is given by:

$$\begin{aligned} \text{Min } w_1 = & \sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{t \in HT_i} c_{ijkt}^1 x_{ijkt} + \sum_{i \in I} \sum_{\ell \in L} \sum_{t \in HT_i} c_{\ell t}^2 y_{ilt} + \\ & \sum_{i \in I} \sum_{\ell \in L} c_{i, a_i}^3 z_{i, \ell, a_i} + \sum_{i \in I} \sum_{\ell \in L} \sum_{t \in HT_i \setminus \{b_i\}} c_{i, t+1}^3 \gamma_{ilt} \end{aligned} \quad (29)$$

$$\text{Min } w_2 = \sum_{i \in I} \sum_{t \in HT_i} h_{it} \quad (2)$$

subject to

$$(5), (7), (10) - (28)$$

$$\sum_{\ell \in L} \sum_{t \in HT_i} Q_{\ell} y_{ilt} = A_i P_i \quad i \in I \quad (30)$$

$$\sum_{j \in J} \sum_{k \in K} C_k^{max} x_{ijkt} - e_{it} = \sum_{\ell \in L} Q_{\ell} y_{ilt} \quad i \in I, t \in HT_i \quad (31)$$

$$\sum_{i \in I_t} \sum_{j \in J} x_{ijkt}^c \leq V_{kt}^{max} \quad k \in K, t \in T \quad (32)$$

$$x_{ijkt}^c + z_{ilt} \leq (V_{kt}^{max} + M_{\ell t}^{max}) s_{it} \quad i \in I, j \in J, k \in K,$$

$$\sum_{j \in J} \sum_{k \in K} x_{ijkt}^c \geq s_{it} \quad \ell \in L, t \in HT_i \quad (33)$$

$$\alpha_{iltr} \in \{0, 1\} \quad i \in I, t \in HT_i \quad (34)$$

$$x_{ijkt}^c \geq 0 \text{ and integer} \quad i \in I, \ell \in L, t \in HT_i, r \in R_{\ell t} \quad (35)$$

$$\gamma_{ilt} \geq 0 \quad i \in I, j \in J, k \in K, t \in HT_i \quad (36)$$

$$y_{ilt} \geq 0 \quad i \in I, \ell \in L, t \in HT_i \setminus \{b_i\} \quad (37)$$

$$\beta_{iltr} \geq 0 \quad i \in I, \ell \in L, t \in HT_i \quad (38)$$

$$\beta_{iltr} \geq 0 \quad i \in I, \ell \in L, t \in HT_i, r \in R_{\ell t} \quad (39)$$

Observe that it is not necessary to explicitly enforce integrality constraints on the new variables  $\gamma_{ilt}$  as they satisfy this property due to constraints (14) and (16).

Finally, we remark that the linearization techniques result in a significant increase in the total number of variables and constraints. This aspect will be highlighted in Section 5 by comparing the sizes of the MINLP and MILP formulations for the instances considered in our numerical study.

### 3.4 An illustrative example

In this section, we present a small example problem and display the main features of two Pareto-optimal solutions. The latter are obtained through lexicographical ordering (see (40)–(43) in Section 4) for the purpose of highlighting the trade-offs between the two conflicting objectives. We have used the optimization solver IBM ILOG CPLEX 12.8 to identify these solutions.

We consider  $|T| = 2$  time periods,  $|I| = 4$  fields,  $|J| = 2$  sugar mills, and  $|K| = |L| = 2$  types of transport vehicles as well as two types of mechanical harvesters. The time window for harvesting each field spans the whole planning horizon, i.e.,  $HT_i = \{1, 2\}$  for every  $i = 1, \dots, 4$ . Moreover, within this time frame,  $A_i P_i = 1,680$  tonnes of sugarcane need to be harvested in each field  $i$  and transported to the mills. In the first (second) time period, both mills have a demand for  $d_{j1} = 1,500$  ( $d_{j2} = 1,700$ ) tonnes of cane ( $j = 1, 2$ ). Hence, total supply exceeds total demand by 320 tonnes. We assume that there is enough harvest and transport equipment available to complete all the operations over the planning horizon. The operating time of a harvester ranges from  $h_t^{min} = 4$  hours to  $h_t^{max} = 16$  hours per period ( $t = 1, 2$ ). Regarding the hourly capacity of the harvest equipment, we take  $Q_1 = 20$  tonnes and  $Q_2 = 30$  tonnes. Vehicles of type 1, resp. type 2, can transport up to  $C_1^{max} = 60$  tonnes, resp.  $C_2^{max} = 75$  tonnes

of sugarcane. Their working hours coincide with the operating hours of the harvesters. Further relevant data are reported in Appendix A which are also used in the larger test instances in the numerical experiments presented in Section 5.

Figure 2 displays the optimal values of the variables in the lexicographic solution that corresponds to assigning higher priority to the total cost over the total harvest time ( $w_1 >_{\text{lex}} w_2$ ). This solution is denoted hereafter ‘lex. sol. 1’. Figure 3 shows the optimal values of the variables in the second lexicographic solution (henceforth called ‘lex. sol. 2’). In this case, the total harvest time is given higher preference over the total cost ( $w_2 >_{\text{lex}} w_1$ ). We note that the values of the continuous variables  $h_{it}$  displayed in Figure 3 were rounded up.

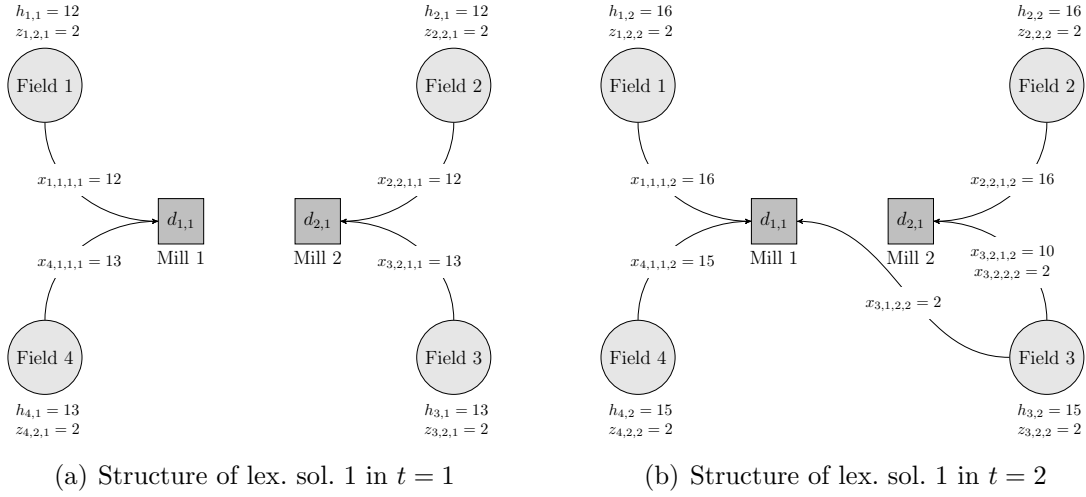


Figure 2: Time dedicated to harvesting each field ( $h_{it}$ ), number of machines of each type assigned per field ( $z_{ilt}$ ), and number of vehicle round trips planned between the fields and the mills ( $x_{ijkt}$ ) when the objective function  $w_1$  is given the highest preference.

Table 3 reports the time dedicated to harvesting the individual fields in each time period (columns 3-4) according to each lexicographic solution. The associated total quantity of sugarcane harvested is shown in columns 5-6 and is given by  $\sum_{\ell=1}^2 Q_{\ell} h_{it} z_{ilt}$  for  $i = 1, 2$  and  $t = 1, 2$ . Columns 7-10 display the quantities of sugarcane delivered to the mills over the planning horizon. Unsurprisingly, there is a striking difference between the number of hours allocated to harvest operations in each solution, which, in turn, impact the tactical planning of vehicle deployment and utilization. Specifically, mechanical harvesters are operated longer when highest preference is given to minimizing the total cost (12 to 16 hours per period or 75-100 percent of the maximum time available).

Table 4 summarizes the type and amount of equipment prescribed by each lexicographic

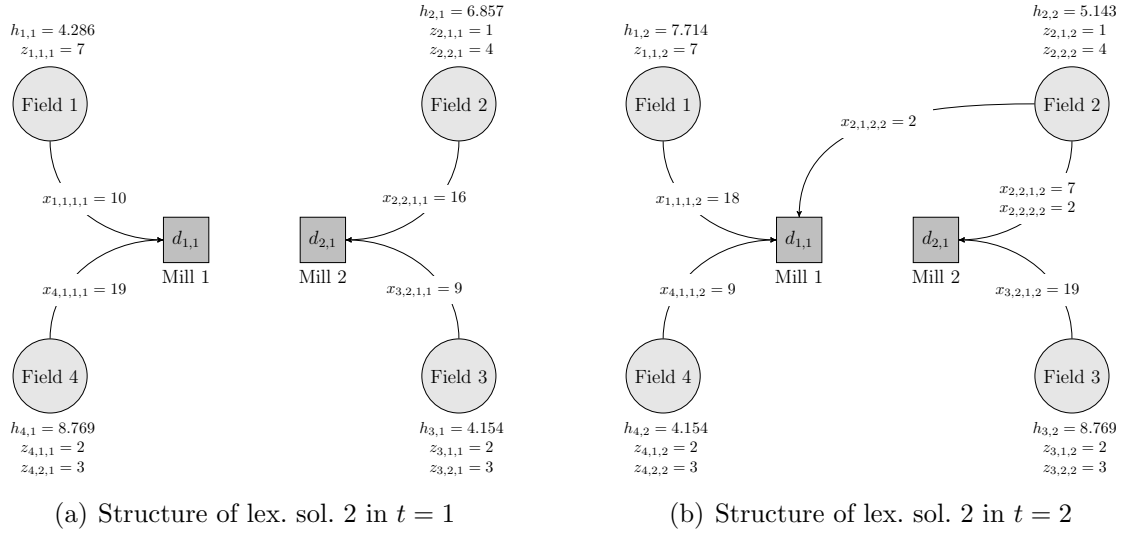


Figure 3: Time dedicated to harvesting each field ( $h_{it}$ ), number of machines of each type assigned per field ( $z_{ilt}$ ), and number of vehicle round trips planned between the fields and the mills ( $x_{ijkt}$ ) when the objective function  $w_2$  is given the highest preference.

Lex. sol.	Field	Harvest time (h)		Quantity harvested (t)		Quantity transported (t)			
		$t = 1$	$t = 2$	$t = 1$	$t = 2$	Mill 1		Mill 2	
						$t = 1$	$t = 2$	$t = 1$	$t = 2$
1	1	12.000	16.000	720	960	720	960	-	-
	2	12.000	16.000	720	960	-	-	720	960
	3	13.000	15.000	780	900	-	150	780	750
	4	13.000	15.000	780	900	780	900	-	-
2	1	4.286	7.714	600	1,080	600	1,080	-	-
	2	6.857	5.143	960	720	-	150	960	570
	3	4.154	8.769	540	1,140	-	-	540	1,140
	4	8.769	4.154	1,140	540	1,140	540	-	-

Table 3: Harvest time and quantity of sugarcane harvested and transported to the mills according to the lexicographic solutions.

solution along with their deployment. Columns 2–3 indicate the total number of harvesting machines of each type that are operated across all fields over the two time periods. Columns 4–5 report the total time the harvesters of each type are operated, i.e.,  $\sum_{i=1}^4 \sum_{t=1}^2 h_{it} z_{ilt}$  for  $\ell = 1, 2$ . Column 6 gives the average operating time per harvester and per period. The total number of vehicles of type 1 and type 2 used are presented in columns 7 and 8, respectively,



which are determined by  $\sum_{i=1}^4 \sum_{j=1}^2 \sum_{t=1}^2 [n_{ijkt} x_{ijkt}]$  ( $k = 1, 2$ ). Columns 9–10 show the total number of round trips made by the vehicles of each type. Finally, columns 11–12 display the total time engaged by the vehicles to commute between the mills and the sugarcane fields.

As expected from the results reported in Table 3 and Figures 2–3, the deployment of the mechanical harvesters differs significantly between the two lexicographic solutions. In order to finish harvesting sooner, a significantly larger number of machines are used in the lex. sol. 2. Specifically, in total 12 harvesters of type 1 (seven in field 1, one in field 2, two in field 3, and two in field 4) and 10 harvesters of type 2 (four in field 2, three in field 3, and three in field 4) are operated. Together, these 22 machines have a total operating time of 273.24 hours ( $147.7 + 125.54$ ) over the two periods, which is about 22% higher than the working time of the harvest equipment selected in the lex. sol. 1 (224 h). In the latter solution, each field is harvested by two large machines in every period. Concurrently, the average operating time of a machine per period is 55.6% lower in the lex. sol. 2. This feature has practical relevance because a lower utilization rate results in reduced maintenance and repair costs for an individual machine. On the other hand, the workforce needed to operate the harvest equipment increases. Regarding the choice of road vehicles, there is no striking difference between the two lexicographic solutions. For example, two large vehicles ( $k = 2$ ) are operated in both solutions in period 2, but they are allocated to different fields. In the lex. sol. 1, each large vehicle makes two round trips between field 3 and one of the mills, while in the lex. sol. 2, the same number of round trips are completed but between field 2 and the mills.

Lex. sol.	No. of harvesters		Operating time (h)		Avg. oper. time per harvester & period (h)	No. of vehicles		No. of round trips		Total travel & service time (h)	
	$\ell = 1$	$\ell = 2$	$\ell = 1$	$\ell = 2$		$k = 1$	$k = 2$	$k = 1$	$k = 2$	$k = 1$	$k = 2$
1	-	8	-	224.00	14.00	29	2	107	4	379.84	19.51
2	12	10	147.70	125.54	6.21	27	2	107	4	363.33	18.84

Table 4: Deployment of harvest and transport resources in the lexicographic solutions.

Table 5 gives information about the two objective functions. Columns 2–7 report the values of the individual components of the cost function, and column 8 presents the total cost,  $w_1$ . The last column displays the total harvest time,  $w_2$ . The trade-offs that are achieved by the two lexicographic solutions are again noticeable in this table. When the economic objective is given the highest importance, the total cost incurred by the harvest and transport operations is 5.6% lower, but at the same time, it takes considerably longer to harvest all the fields (the total harvest time increases by a factor of 2.5). As mentioned earlier, these differences are

attributed to the choice of harvest equipment. Using more harvesters (of both types) results in higher operating costs and most of all, in more expensive transports of the machines between the depot and the fields.

Lex. sol.	Harvest cost (m.u.)				Transport cost (m.u.)		Total cost (m.u.)	Total harvest time (h)
	Machine operation		Machine transfer		$k = 1$	$k = 2$		
	$\ell = 1$	$\ell = 2$	$\ell = 1$	$\ell = 2$				
1	-	55,104.0	-	755.4	46,657.0	2,383.0	104,899.4	112.0
2	31,899.0	30,879.0	1,755.0	2,188.0	42,200.0	2,183.0	111,104.0	49.8

Table 5: Harvest costs and harvest times associated with the lexicographic solutions.

## 4 Solution methodology

In this section, we describe an exact method to find Pareto-optimal solutions to the problem introduced in Section 3.3. Our solution approach extends the *Progressive Bounded Constraint* (PBC) method proposed by Gonçalves et al. (2019) for a bi-objective optimization problem arising in the generation of electricity, where total fuel cost and greenhouse gas emissions are minimized while satisfying various operational constraints. Next, we outline this method, adapt it to our problem, and motivate its extension.

Let us consider the following general form of a bi-objective optimization problem:

$$\begin{aligned}
 & \text{Min } w_1 = f_1(x) \\
 & \text{Min } w_2 = f_2(x) \\
 & \text{subject to} \\
 & \quad x \in \Omega \subseteq \mathbb{R}^n,
 \end{aligned}$$

where  $x$  is a decision vector with  $n$  variables,  $f_i : \mathbb{R}^n \mapsto \mathbb{R}$  is the  $i$ -th objective function ( $i = 1, 2$ ), and  $\Omega$  denotes the feasible region defined by a given set of constraints. Moreover, let  $W = \{w = (f_1(x), f_2(x)) \in \mathbb{R}^2 : x \in \Omega\}$  be the *objective space* represented by the set of points in  $\mathbb{R}^2$  that result from mapping  $\Omega$  onto the functions  $f_1$  and  $f_2$ . Any point  $w \in W$  is associated with at least a specific feasible solution to the original problem. In our case,  $f_1$  and  $f_2$  are represented by (29) and (2), respectively, and  $\Omega$  is given by (5), (7), (10)-(28), (30)-(39).

The general idea of the PBC method is to divide the objective space  $W$  into a fixed number of non-overlapping subregions called *bands*, and identify non-dominated points in each subregion. The latter are associated with Pareto-optimal solutions to the original bi-objective problem. The objective space  $W$  can be divided either into horizontal or vertical bands. For our specific problem, we have opted to generate horizontal bands as illustrated in Figure 4 (we note that the procedure to be detailed next can be easily adapted to a vertical decomposition of  $W$ ). For this purpose, the subproblem that minimizes  $f_1(x)$  is selected and extended with so-called *band constraints* that impose a lower and an upper bound on the second objective function,  $f_2(x)$ . These bounds are related to the subregion that is inspected. In this way, a sequence of independent single-objective subproblems are solved that allow us to gradually construct (an approximation of) the Pareto front, depending on the number of subregions the objective space is partitioned.

We start by identifying the extreme points in the Pareto front associated with the lexicographic solutions. The so-called *left lexicographic solution*  $x_1^*$  is determined by solving the following subproblems (40) and (41) sequentially, which correspond to taking  $f_1 >_{\text{lex}} f_2$ .

$$\begin{array}{ll}
 \bar{x}_1 = \operatorname{argmin}\{f_1(x)\} & (40) \\
 \text{subject to} & \\
 x \in \Omega. & 
 \end{array}
 \qquad
 \begin{array}{ll}
 x_1^* = \operatorname{argmin}\{f_2(x)\} & (41) \\
 \text{subject to} & \\
 f_1(x) \leq f_1(\bar{x}_1) & \\
 x \in \Omega. & 
 \end{array}$$

The counterpart of  $x_1^*$  is the *right lexicographic solution*  $x_2^*$ , which is obtained in a similar way by imposing  $f_2 >_{\text{lex}} f_1$ .

$$\begin{array}{ll}
 \bar{x}_2 = \operatorname{argmin}\{f_2(x)\} & (42) \\
 \text{subject to} & \\
 x \in \Omega. & 
 \end{array}
 \qquad
 \begin{array}{ll}
 x_2^* = \operatorname{argmin}\{f_1(x)\} & (43) \\
 \text{subject to} & \\
 f_2(x) \leq f_2(\bar{x}_2) & \\
 x \in \Omega. & 
 \end{array}$$

The images of  $x_1^*$  and  $x_2^*$  in  $W$  are denoted  $w_1^*$  and  $w_2^*$ , respectively. The determination of solutions  $x_1^*$  and  $x_2^*$  allows the elimination of weakly non-dominated solutions, and consequently,

of weakly non-dominated points in the objective space. The latter are illustrated in Figure 4 by  $\bar{w}_1$  and  $\bar{w}_2$ .

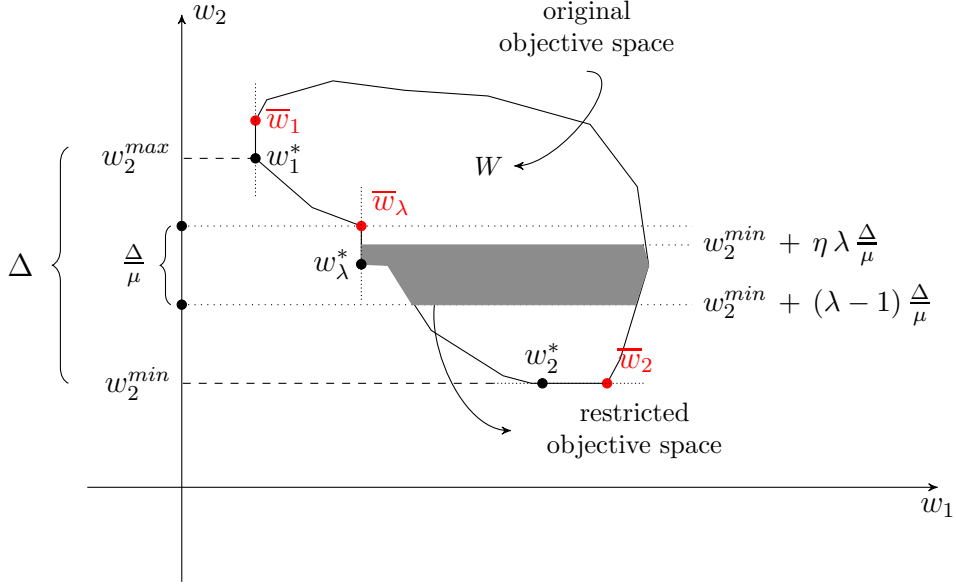


Figure 4: Extended PBC method with horizontal bands.

Next, we define the interval  $I = [w_2^{\min}, w_2^{\max}]$ , with length  $\Delta$ , and whose boundaries are the projection of the images of the left and right lexicographic solutions on the  $w_2$ -axis, as shown in Figure 4. The interval  $I$  is then divided into a pre-specified number  $\mu \in \mathbb{Z}_+$  of subintervals of equal length  $\Delta/\mu$ . The  $\lambda$ -th subinterval ( $\lambda = 1, 2, \dots, \mu$ ) is associated with a horizontal band whose boundaries are given by

$$w_2^{\min} + (\lambda - 1) \frac{\Delta}{\mu} \leq f_2(x) \leq w_2^{\min} + \eta \lambda \frac{\Delta}{\mu}, \quad (44)$$

with  $\eta$  a parameter such that  $(\lambda - 1)/\lambda < \eta < 1$ . Hence, the objective space  $W$  is partitioned into  $\mu$  horizontal, non-overlapping bands,  $W_1, W_2, \dots, W_\mu$ , where  $W_\lambda = \{w \in \mathbb{R}^2 : W \cap (44)\}$  for every  $\lambda = 1, 2, \dots, \mu$ .

For a given  $\lambda$ , let  $w_\lambda^*$  be a non-dominated point in the restricted objective space  $W_\lambda$  (see Figure 4), whose pre-image is associated with a Pareto-optimal solution to the original bi-objective problem. To find  $w_\lambda^*$ , it is necessary to solve two single-objective subproblems sequentially. First, subproblem (45) is solved. Its optimal solution  $\bar{x}_\lambda$  is mapped into the associated band  $W_\lambda$ . As illustrated in Figure 4, this point is located as left as possible in the  $\lambda$ -th subregion, corresponding to the minimum value for  $f_1(x)$ . Next, we solve subproblem (46) and obtain

its optimal solution  $x_\lambda^*$ , whose image is the point  $w_\lambda^*$  in the restricted objective space  $W_\lambda$ . As displayed in Figure 4, the position of  $w_\lambda^*$  is the lowest in the direction of the  $w_2$ -axis for the value of  $w_1 = f_1(\bar{x}_\lambda)$  determined by (45).

$$\begin{array}{ll}
\bar{x}_\lambda = \operatorname{argmin}\{f_1(x)\} & (45) \\
\text{subject to} & \\
(44) & \\
x \in \Omega. & 
\end{array}
\qquad
\begin{array}{ll}
x_\lambda^* = \operatorname{argmin}\{f_2(x)\} & (46) \\
\text{subject to} & \\
(44) & \\
f_1(x) \leq f_1(\bar{x}_\lambda) & \\
x \in \Omega. & 
\end{array}$$

Observe that small values of  $\lambda$  contribute to finding a solution  $x_\lambda^*$  that gives more relevance to the minimization of  $w_2$ . As the value of  $\lambda$  increases, the minimization of  $w_1$  gradually becomes more important. Parameter  $\mu$  controls the maximum number of non-dominated solutions that are identified. The larger the value of  $\mu$ , the more subregions are inspected, and the more points can be determined. In total,  $2\mu$  single-objective subproblems need to be solved, i.e.,  $\mu$  subproblems of type (45) and  $\mu$  subproblems of type (46). Moreover, the distance between non-dominated points is controlled by parameter  $\eta$  in (44), which extends the boundaries proposed by Gonçalves et al. (2019) for the  $\lambda$ -th subinterval. In fact, the original PBC method corresponds to the special case of imposing  $\eta = 1$ . Parameter  $\eta$  reduces the upper bound on  $f_2(x)$  and ensures that  $W_\lambda \cap W_{\lambda'} = \emptyset$  for  $\lambda \neq \lambda'$ . If  $W_\lambda \neq \emptyset$  for a given  $\lambda$  then a new Pareto-optimal solution can be identified which differs from the one found in the previous subregion  $\lambda - 1$ . This is achieved by solving the single-objective subproblem (46) which allows us to eliminate all weakly non-dominated solutions that could be found when subproblem (45) was solved. By contrast, in the original PBC method the same Pareto-optimal solution could be obtained in adjacent bands because by construction, the intersection of the restricted objective spaces  $W_{\lambda-1}$  and  $W_\lambda$  could be non-empty. Hence, the introduction of parameter  $\eta$  into the upper bound in (44) results in an improvement over the original version of the PBC method.

Figure 4 shows geometrically how the extended PBC strategy works and highlights the elimination of weakly non-dominated points (i.e.,  $\bar{w}_1$ ,  $\bar{w}_2$ , and  $\bar{w}_\lambda$ ) while solving multiple subproblems. Algorithm 1 details the steps that need to be carried out in order to obtain a set  $\chi$  of Pareto-optimal solutions to our bi-objective MILP problem. The selection of particular values for the parameters  $\mu$  and  $\eta$  will be discussed in Section 5.

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**Algorithm 1:** Extended progressive bounded constraint method

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**Input:**  $f_1$  defined by (29),  $f_2$  defined by (2),  $\Omega$  represented by (5), (7), (10)-(28), and (30)-(39),  $\mu, \eta$

**Output:** Set of Pareto-optimal solutions,  $\chi$

- 1 Obtain the left lexicographic solution  $x_1^*$  by solving subproblems (40) and (41), and determine the associated image  $w_1^*$  along with its projection  $w_2^{max}$  on the  $w_2$ -axis of the objective space  $W$ ;
  - 2 Obtain the right lexicographic solution  $x_2^*$  by solving subproblems (42) and (43), and determine the associated image  $w_2^*$  along with its projection  $w_2^{min}$  on the  $w_2$ -axis of the objective space  $W$ ;
  - 3  $I \leftarrow [w_2^{min}, w_2^{max}]$ ;
  - 4  $\Delta \leftarrow w_2^{max} - w_2^{min}$ ;
  - 5  $\chi \leftarrow \emptyset$ ;
  - 6 **for**  $\lambda \leftarrow 1$  **to**  $\mu$  **do**
  - 7     Calculate the lower and upper bounds in (44);
  - 8     Solve subproblems (45) and (46) to obtain a Pareto-optimal solution  $x_\lambda^*$  and determine its associated image  $w_\lambda^*$  in the restricted objective space  $W_\lambda$ ;
  - 9      $\chi \leftarrow \chi \cup \{x_\lambda^*\}$
  - end**
- 

In our computational study, we have used the general-purpose optimization solver CPLEX to solve the MILP subproblems required by the above algorithm. Preliminary tests have shown that it can be computationally expensive to solve these subproblems to optimality or to even find feasible solutions satisfying a given optimality gap. In particular, the subproblems involving the minimization of the total harvest time ( $w_2$ ) proved to be challenging. To reduce the computational burden, we have adopted the strategy of supplying CPLEX with an initial (feasible) solution whenever a given subproblem needs to be solved. At first, the left lexicographic solution  $x_1^*$  is obtained by providing to CPLEX the optimal solution  $\bar{x}_1$  to (40) and then solving (41). Next, solution  $x_1^*$  is supplied to CPLEX and subproblem (42) is solved. Its optimal solution  $\bar{x}_2$  is used as an initial solution to obtain the right lexicographic solution  $x_2^*$  when solving (43). Furthermore, for each  $\lambda$  in Algorithm 1 (lines 6–9), the Pareto-optimal solution identified in the previous step, i.e.,  $x_{\lambda-1}^*$ , is used as an initial solution for solving subproblem (45). For the particular case of  $\lambda = 1$ ,  $x_2^*$  is taken as the initial solution. Due to the band constraints (44),  $x_{\lambda-1}^*$  may be infeasible to (45). However, CPLEX is able to repair this solution and thus restore feasibility within an acceptable computing time. Subproblem (46) uses  $\bar{x}_\lambda$  as the initial solution. Preliminary numerical experiments have indicated that the linear

relaxation of the original subproblems provides relatively weak lower bounds, thus justifying the adoption of the procedure just described. Finally, we observe that other solution approaches have also been tried, namely the linear weighting procedure, the  $\varepsilon$ -constraint method, and the Chebyshev scalarization technique, but all performed rather poorly. As will be shown in the next section, the extended PBC method proved to be an attractive alternative for identifying a set of Pareto-optimal solutions. Not only is the method numerically more stable but also the search for an efficient solution is guided in a more precise way compared to other procedures such as the  $\varepsilon$ -constraint method.

## 5 Computational study

In this section, we present the results of computational experiments performed for a set of semi-randomly generated instances that capture the characteristics of the sugarcane harvest and transport operations in Brazil. In Section 5.1, we briefly describe the methodology developed to obtain these instances, followed by the analysis of the numerical results in Section 5.2. In addition, relevant managerial insights into the tactical sugarcane harvest and transport planning problem are discussed in Section 5.3.

### 5.1 Test instances

Information on harvest and transport logistics was collected through a series of interviews and discussions with a consulting firm that offers software solutions to a milling company in the state of São Paulo, Brazil. Figure 5 shows the locations of two mills ( $|J| = 2$ ) and 30 sugarcane fields managed by the company. The location of the depot where harvest equipment is stored, is also displayed. A system of orthogonal coordinates was used whose origin is represented by the location of mill 1. The values of parameters  $D_{ij}$  and  $D_i^0$  ( $i \in I, j \in J$ ) correspond to real travel distances that take into account the type of roads used by the transport vehicles and the equipment that carries the mechanical harvesters to the fields. Further parameters were obtained by randomly selecting their values within ranges that were derived from historical data provided by our consulting partner and official sources. Details are given in Appendix A.

Three values for the set  $I$  were considered that differ in the area covered by the milling operations. Instances with  $|I| = 10$  include the sugarcane fields located north-west of mill 1, numbered 1–10 in Figure 5. Instances with  $|I| = 20$  comprise the fields in the north-west and

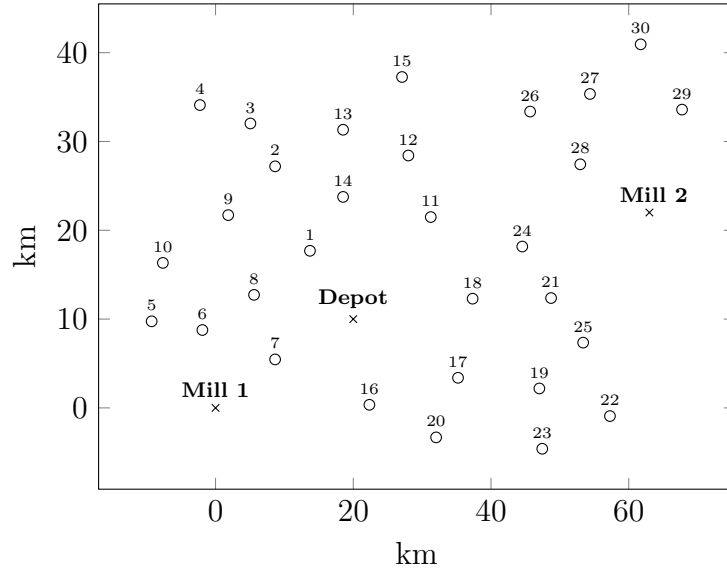


Figure 5: Milling area: locations of sugarcane fields, sugar mills, and the depot for storing mechanical harvesters.

central regions (locations 1 to 20). In the third type of instances, the whole milling area is covered ( $|I| = 30$ ). In instances with  $|I| \in \{10, 20\}$ , all harvested cane is transported to mill 1, whereas in the largest instances both mills are operated. As it will be shown in Section 5.2, the size of these semi-randomly generated instances and the associated computational burden to obtain Pareto-optimal solutions are greatly affected by these choices.

In all instances, the planning horizon spans one month which is divided into 30 working days (i.e.,  $|T| = 30$ ). Therefore, in addition to weekdays, harvest operations can also take place on Saturdays and Sundays. It is assumed that the sugarcane will reach its maturity peak over this time horizon. Individual time windows for harvesting the fields ( $HT_i, i \in I$ ) are selected according to Table 12 in Appendix A. They reflect the estimated days closest to the maximum sucrose content, which, in turn, depend on the different cane varieties grown. The areas of the fields and their expected productivity are obtained according to Table 12, which also indicates how the demands for sugarcane at the mills are generated.

Three scenarios are considered that differ in the operating time of the harvest and transport equipment available over the planning horizon. These scenarios will enable a comparative analysis of the associated tactical plans in terms of economic performance and harvest efficiency. In the *adverse weather* (AW) scenario, it is assumed that unfavorable weather conditions (e.g., rain) will occur in the first week, thereby strongly limiting the harvest operations. As shown in



Table 6, each harvesting machine can work at least one hour and at most four hours in periods 1 to 7. In all other periods, the harvesters' operating time ranges from four to 16 hours. This corresponds to working two eight-hour shifts per day, including weekends, to compensate for the reduced working hours in the first week. The *regular schedule* (RS) scenario considers a regular work schedule according to the Brazilian labor legislation for the sugarcane industry, and also assumes favorable weather conditions during the whole planning horizon. This means that two eight-hour shifts on weekdays and one eight-hour shift on weekends are operated. Finally, the third scenario, *extended schedule* (ES), allows one additional eight-hour shift on Saturdays and Sundays. In all scenarios, the availability of the transport vehicles is affected by a number of factors, e.g., road restrictions due to construction works, congestion, and closures, vehicle breakdown, refueling, stop-and-check operations by the police, etc. As a result, the maximum transport time of a vehicle is randomly drawn from a normal distribution with expected value  $\mu$  and standard deviation  $\sigma$ , denoted  $\mathcal{N}(\mu, \sigma)$ . Table 6 gives the values of  $\mu$  and  $\sigma$  that are selected for each scenario, based on historical data.

Parameter	Adverse weather scenario		Regular schedule scenario		Extended schedule scenario
	First week	Other weeks	Weekdays	Weekend	All days
$h_t^{min}$	1	4	4	4	4
$h_t^{max}$	4	16	16	8	16
$hv_t^{max}$	$\mathcal{N}(4, 1)$	$\mathcal{N}(16, 1)$	$\mathcal{N}(16, 1)$	$\mathcal{N}(8, 1)$	$\mathcal{N}(16, 1)$

Table 6: Harvest and transport operating times available in the different scenarios and all periods  $t \in T$ .

By combining the three scenarios with  $|I| \in \{10, 20, 30\}$ , nine test instances are obtained. All instances share two types of harvesting machines ( $|L| = 2$ ) and three types of vehicles ( $|K| = 3$ ). Their characteristics are given in Tables 13 and 14 in Appendix A, along with the associated operating costs and hourly wages. In accordance with Brazilian labor laws, the latter include a 50 percent and a 100 percent premium for hours worked on Saturdays and Sundays, respectively.

## 5.2 Numerical results

The bi-objective MILP formulation proposed in Section 3.3 was implemented with the JuMP modeling language (version v0.20, Dunning et al. (2017)) and embedded in the Julia programming language (version 1.0.4, Bezanson et al. (2017)). All experiments were performed on a

laptop computer with a 2.5 GHz Intel Core i7-2450M processor, 8 GB RAM, and running a 64-bit operating system. Subproblems (40)-(43) and (45)-(46) in Algorithm 1 were solved with IBM ILOG CPLEX 12.8. A limit of 3,600 seconds of CPU time and an optimality gap of 0.01% were set for each solver run.

In all numerical experiments, the objective space  $W$  is divided into  $\mu = 3$  horizontal bands with  $\eta = 0.95$  for bounding each band (44), thus enabling the identification of three Pareto-optimal solutions for each instance (in addition to the lexicographic solutions). This choice is supported by the studies of Aliano Filho et al. (2019) and Florentino et al. (2018) for other multi-objective optimization problems arising in Brazil's sugarcane industry. From a practical viewpoint, these solutions are good representatives of the conflicting nature of the objectives (29) and (2), and therefore, they can assist the decision maker in selecting an appropriate compromise tactical plan. Naturally, the choice of a higher value for  $\mu$  would return a larger number of Pareto-optimal solutions, but at the cost of extensive computational effort and a lengthy comparative analysis. Observe that when  $\lambda = 1$ , a Pareto-optimal solution is identified that presents a higher compromise toward the minimization of the objective  $w_2$  in (2), i.e., the total harvest time. For  $\lambda = 3$ , the associated Pareto-optimal solution has the opposite attribute, and the compromise is more significant toward minimizing the total cost  $w_1$  in (29). For  $\lambda = 2$ , the associated Pareto-optimal solution exhibits a balanced compromise with respect to both objectives. Note that for simplicity, we will use the term Pareto optimality regarding the solutions returned by Algorithm 1, even though the optimality of every solution is not always guaranteed due to the stopping criteria specified for the optimization solver. Along with the lexicographic solutions, the resulting subset of (five) alternative Pareto-optimal solutions is large enough to support the decision maker in understanding the relevant trade-offs between cost performance and harvest efficiency, thereby supporting a more informed choice of the preferred solution to be implemented. This aspect will be discussed later in this section and further details will be provided in Section 5.3.

For each number of sugarcane fields considered, Table 7 presents the total number of variables and constraints in the non-linear formulation (columns 2–4) and in the equivalent linear formulation (columns 5–7). Furthermore, for each value of  $\lambda$  (column 8), the average number of branch-and-bound nodes visited by CPLEX, the average optimality gap, and the average CPU time are reported in columns 9, 10, and 11, respectively. Notice that running Algorithm 1 for each instance requires solving 10 subproblems. Hence, in total, 90 subproblems were solved. As expected, the linearization techniques introduced in Section 3.3 greatly affect

the size of the associated MILP model, yielding formulations with 3-3.5 times more integer variables and nine times more continuous variables. The total number of constraints grows, on average, by a factor of 3.3. Despite the very large number of integer-valued variables, Algorithm 1 enhanced with the procedure described at the end of Section 4 for solving the subproblems has proved to be very efficient, as demonstrated by the rather small optimality gaps. Interestingly, the number of nodes and the CPU times reported by CPLEX suggest that minimizing the total harvest time ( $w_2$ ) is computationally more expensive than minimizing the total cost ( $w_1$ ).

I	MINLP formulation		MILP formulation		$\lambda$	Performance				
	# variables		# constraints			# nodes	Gap (%)	CPU (s)		
	int.	cont.	int.	cont.						
10	768	256	2,671	2,688	2,304	8,907	1	25,240	0.00	627.63
							2	7,298	0.00	132.73
							3	3,391	0.00	81.46
20	1,518	506	5,131	5,313	4,554	17,447	1	29,899	0.02	3,600.00
							2	19,151	0.01	3,600.00
							3	13,755	< 0.01	2,001.13
30	3,474	772	10,186	10,422	6,948	31,314	1	35,799	0.04	3,600.00
							2	23,595	0.02	3,600.00
							3	18,059	< 0.01	3,352.00

Table 7: Size of test instances, average optimality gap, and average CPU time.

Table 8 gives the objective function values of the solutions obtained. The total cost and the total harvest time are reported in columns 4 and 8, respectively, for each combination of the number of sugarcane fields (column 1), value of  $\lambda$  (column 2), and scenario (column 3). The best objective values are shown in boldface. Moreover, the relative contribution of the different cost components to the total cost is given in columns 5–7. The conflicting nature of the two objectives is clearly reflected in the results obtained, regardless of the scenario. For the smallest instances with 10 fields, the normal working schedule yields the lowest total cost in all Pareto-optimal solutions. By contrast, the lowest expenditure is achieved by the extended working schedule for the largest instances with 30 fields. For the medium-sized instances with 20 fields, the lowest total cost is affected by the value of  $\lambda$ . In all solutions obtained, the cost of operating the harvesting machines makes up the largest share, with an average of 65.7 percent, followed by the cost incurred by the round trips made by the vehicles, which accounts, on average, for 33.4 percent. As expected, moving the harvesters between the depot and the fields has the

I	$\lambda$	Scenario	Cost function			Total harvest time (h)	
			Total cost (R\$)	% of total cost			
				Vehicle transports	Machine operation		Machine transports
10	1	Adverse weather	985,325	31.4	67.5	1.1	<b>534.32</b>
		Normal schedule	<b>981,336</b>	31.4	67.7	0.9	609.24
		Extended schedule	986,005	31.4	67.7	0.9	573.78
	2	Adverse weather	984,396	31.6	67.6	0.8	<b>827.00</b>
		Normal schedule	<b>979,019</b>	31.5	67.9	0.6	917.88
		Extended schedule	982,584	31.5	67.9	0.6	864.76
	3	Adverse weather	983,377	31.5	67.7	0.8	<b>1,017.43</b>
		Normal schedule	<b>978,306</b>	31.5	67.9	0.6	1,217.28
		Extended schedule	982,130	31.5	68.0	0.5	1,155.13
20	1	Adverse weather	2,142,299	37.3	61.7	1.1	<b>1,847.08</b>
		Normal schedule	<b>2,107,159</b>	37.8	61.5	0.8	1,926.33
		Extended schedule	2,109,580	37.7	61.5	0.8	1,884.65
	2	Adverse weather	2,108,430	37.8	61.3	0.9	<b>1,770.55</b>
		Normal schedule	<b>2,093,634</b>	38.0	61.4	0.6	2,221.09
		Extended schedule	2,099,935	37.8	61.5	0.7	2,185.66
	3	Adverse weather	2,088,971	38.1	61.2	0.7	<b>2,192.56</b>
		Normal schedule	2,083,275	38.1	61.4	0.5	2,517.97
		Extended schedule	<b>2,079,250</b>	38.2	61.3	0.5	2,486.70
30	1	Adverse weather	3,080,312	32.4	66.5	1.2	<b>3,116.70</b>
		Normal schedule	3,089,210	32.4	66.4	1.2	3,118.92
		Extended schedule	<b>3,072,366</b>	32.2	66.6	1.2	3,266.54
	2	Adverse weather	3,068,912	32.6	66.2	1.1	<b>3,189.83</b>
		Normal schedule	3,081,241	32.3	66.6	1.2	3,382.92
		Extended schedule	<b>3,062,020</b>	32.4	66.5	1.1	3,359.54
	3	Adverse weather	3,062,523	32.5	66.3	1.2	<b>3,210.12</b>
		Normal schedule	3,070,048	32.5	66.4	1.2	3,636.23
		Extended schedule	<b>3,061,806</b>	32.3	66.6	1.1	3,570.51

Table 8: Objective values of the solutions obtained.

smallest contribution, which ranges from 0.5 to 1.2 percent of the total cost. Regarding the total time dedicated to harvesting the fields, the adverse weather scenario requires the smallest number of hours in all instances and for  $\lambda = 1$ . Recall that the availability of the harvesting equipment is the lowest in this scenario. This feature together with the higher relevance given to minimizing the total harvest time when  $\lambda = 1$ , explains this outcome. Furthermore, significant

differences in the harvest time can be observed among the solutions for a fixed value of  $|I|$ , whereas the total cost does not show remarkable variations. Details are provided in the next section that reveal the main features of the solutions. Table 15 in Appendix B complements Table 8 by reporting the objective values associated with the lexicographic solutions.

To investigate the impact of partitioning the objective space into more than three regions, we have also run Algorithm 1 with  $\mu = 10$  for one of the instances with 10 sugarcane fields. Figure 6 depicts the objective values of the 10 solutions obtained for the normal schedule scenario (marked as squares in the figure). For comparison, the objective values of the Pareto-optimal solutions returned by the algorithm for  $\mu = 3$  are also displayed. These are marked with dots, and their coordinates are given in Table 8 for  $|I| = 10$ ,  $\lambda = 1, 2, 3$ , and the NS scenario. It should be noted that the 10 points are evenly distributed with respect to the objective  $w_2$ . Observe that some of these points are associated with unsupported efficient solutions since the Pareto front does not seem to be convex. The front is steep in the vicinity of the minimum of  $w_1$  (left side) and becomes flatter toward the minimum of  $w_2$  (right side). This means that small changes in total cost ( $w_1$ ) lead to sharp differences in total harvest time ( $w_2$ ), whereas solutions with relatively low harvest times exhibit noticeably different costs. This suggests that our choice of identifying three Pareto-optimal solutions between the two lexicographic solutions provides a reasonably representative, and from a tactical viewpoint, also suitable sample for our problem.

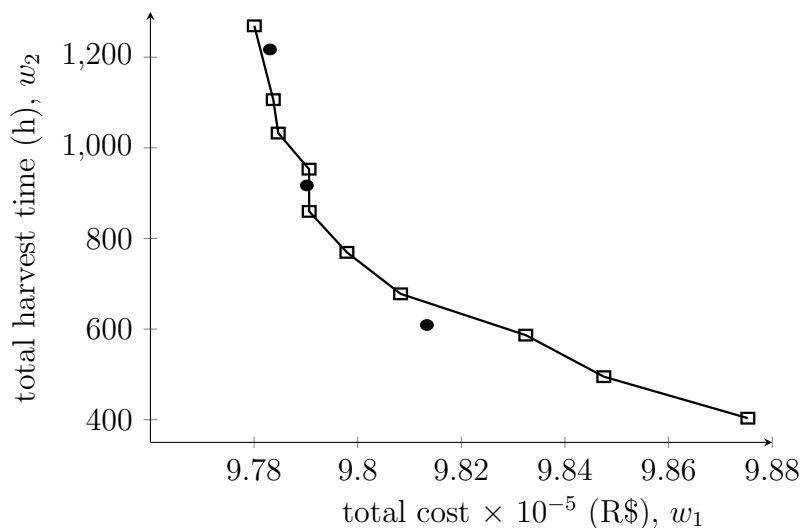


Figure 6: Pareto front with 10 non-dominated points for the instance with 10 fields under the normal schedule scenario.

### 5.3 Managerial insights

The aim of this section is to gain a broader insight into the characteristics of the various solutions identified for each instance. The analysis will help the decision maker to better understand the trade-offs achieved between the two objectives as well as the impact of the different work schedules and weather conditions assumed. Key information will be provided on the type of harvest and transport equipment selected along with its use over the planning horizon.

Table 9 gives the average number of hours driven by a vehicle outside a normal shift per day (i.e., beyond eight hours) in each solution and for the three scenarios (columns 3, 7, and 11). In addition, the average number of road haulage vehicles operated on each field per day is also displayed, according to type. It can be seen that the number of additional hours worked is the greatest in the extended schedule scenario, since this scenario has the largest amount of transport time available over the whole planning horizon (cf. Table 6). Even though the availability of the vehicles in the adverse weather scenario is the same as in the ES scenario in weeks 2–4, the first week offers reduced transport time, thus explaining the smaller average extra work in the AW scenario. The normal schedule scenario displays an intermediate use of additional work in all solutions. In general, the solutions obtained for  $\lambda = 3$  concern tactical plans with less additional transport time, since these solutions favor cost minimization as opposed to the solutions for  $\lambda = 1$ , which emphasize the minimization of the total harvest time.

I	$\lambda$	Adverse weather scenario				Normal schedule scenario				Extended schedule scenario			
		Extra hours		# vehicles		Extra hours		# vehicles		Extra hours		# vehicles	
		per vehicle	$k = 1$	$k = 2$	$k = 3$	per vehicle	$k = 1$	$k = 2$	$k = 3$	per vehicle	$k = 1$	$k = 2$	$k = 3$
10	1	3.88	3.7	0.1	0.0	4.38	2.8	0.1	0.0	5.74	2.5	0.1	0.0
	2	3.46	3.8	0.1	0.0	4.07	2.9	0.1	0.0	4.07	2.5	0.1	0.0
	3	2.99	3.9	0.1	0.0	3.65	2.9	0.1	0.0	5.21	2.6	0.1	0.0
20	1	4.16	3.0	0.8	0.0	4.49	2.7	0.3	0.0	5.64	2.4	0.3	0.0
	2	4.11	2.9	0.9	0.0	4.42	2.7	0.3	0.0	5.48	2.5	0.2	0.0
	3	3.92	3.0	0.8	0.0	4.38	2.7	0.2	0.1	5.60	2.5	0.1	0.0
30	1	3.79	2.1	1.3	0.1	3.99	2.0	1.0	0.0	5.16	1.9	0.7	0.1
	2	3.53	2.1	1.4	0.2	4.02	2.1	0.9	0.1	5.22	1.9	0.7	0.0
	3	3.82	2.1	1.3	0.1	3.96	2.0	0.9	0.1	4.93	1.9	0.7	0.1

Table 9: Average additional hours worked (over 8h/day) by the vehicles and average number of vehicles per type.

Table 9 also provides information regarding the most suitable vehicle profile for the transportation of sugarcane to the mills. In all solutions and scenarios, there is a strong preference

for operating vehicles of type 1. Despite these being the smallest vehicles, they have the advantage of being fast, taking less time to load and unload the cane, and having a lower cost per kilometer driven. Therefore, more round trips can be made with these vehicles per day. The operation of the other two types of vehicles is rather limited, especially the largest type ( $k = 3$ ) is occasionally used in the instances with 30 fields. In addition, no noteworthy differences in the total number of vehicles selected are observed among the solutions obtained. This is due to the fact that the amount of sugarcane transported to the mills is not affected by the number of hours worked by the harvesters.

Table 10 gives the average daily number of hours worked by a mechanical harvester on a field beyond a normal shift, in each solution, and for the three scenarios (columns 3, 6, and 9). Moreover, the average number of machines operated in each field per day is also reported, according to type. Unsurprisingly, solutions for  $\lambda = 3$  are associated with more hours worked beyond a normal shift than solutions for  $\lambda = 1$ . In some cases, the difference is significant (e.g., instances with  $|I| = 10$ ). On average, 40.7, 25.5, and 44.6 percent more extra work is used in the AW, NS, and ES scenarios, respectively, when  $\lambda = 3$ . Regarding the choice of mechanical

$ I $	$\lambda$	Adverse weather scenario			Normal schedule scenario			Extended schedule scenario		
		Extra hours		# harvesters	Extra hours		# harvesters	Extra hours		# harvesters
		per harvester			per harvester			per harvester		
		$\ell = 1$	$\ell = 2$		$\ell = 1$	$\ell = 2$		$\ell = 1$	$\ell = 2$	
10	1	2.29	0.0	5.5	2.50	0.0	5.5	2.06	0.0	5.1
	2	3.16	0.0	3.9	3.17	0.0	3.1	3.43	0.0	3.8
	3	4.17	0.0	3.3	3.40	0.0	2.9	4.52	0.0	2.7
20	1	4.12	0.8	4.0	4.42	0.5	2.9	4.65	0.1	3.0
	2	5.42	0.3	3.7	4.43	0.2	2.6	5.02	0.1	2.6
	3	5.72	0.2	3.4	5.17	0.0	2.5	4.65	0.0	2.4
30	1	4.81	1.9	2.0	3.83	1.0	2.0	4.73	1.3	2.5
	2	5.18	1.4	2.0	4.42	0.9	2.1	5.39	0.7	2.1
	3	4.86	1.4	2.1	4.73	1.1	1.8	5.41	1.1	2.0

Table 10: Average additional hours worked (over 8h/day) by the harvesting machines and average number of machines per type.

harvesters, it can be seen that machines of type 2 are consistently preferred. Although this type of machinery is more expensive, it has a higher cutting speed, thus achieving more throughput in a shorter time (cf. Table 13). Furthermore, and as anticipated, more machines of this type are selected in the compromise solutions for  $\lambda = 1$  since more relevance is assigned to harvest efficiency in these solutions. Harvesters of type 1 are only operated in the instances with 20

and 30 fields. Figures 9–11 in Appendix B complement this analysis by showing the average proportion of machines available that are selected per period. In particular, in the instances with 30 fields, 92.4 percent of the most efficient harvesters and 67 percent of the harvesters of type 1 are operated, on average.

Table 11 provides further insight into the deployment of the harvest equipment. For each value of  $|I|$  and  $\lambda$  (columns 1–2), columns 3, 6, and 9 report the average total number of harvesters used per field and period in the AW, NS, and ES scenarios, respectively. The average number of periods required to harvest a field is given in columns 4, 7, and 10 for each scenario. The remaining columns 5, 8, and 11 display the average number of hours worked on a field per period. In accordance with the results reported in Table 10 for each machine type,

$ I $	$\lambda$	Adverse weather scenario			Normal schedule scenario			Extended schedule scenario		
		# harvesters	# periods	# hours	# harvesters	# periods	# hours	# harvesters	# periods	# hours
10	1	5.3	7.2	7.72	4.5	7.6	8.09	5.3	6.9	8.83
	2	4.3	10.1	8.29	3.1	10.7	9.99	3.2	9.1	10.10
	3	3.7	10.3	10.60	2.8	11.4	10.70	2.8	11.4	10.50
20	1	4.8	6.4	10.76	3.4	8.0	11.44	3.1	8.6	11.47
	2	3.9	7.1	12.53	2.8	9.5	11.44	2.7	9.5	11.93
	3	3.5	8.4	12.85	2.5	10.2	12.29	2.5	10.1	12.22
30	1	3.3	9.4	11.64	2.9	10.8	10.68	3.8	8.6	11.85
	2	3.2	9.7	12.07	3.1	10.1	11.61	3.3	9.3	12.60
	3	3.2	9.1	11.70	2.9	10.0	12.07	3.1	9.6	12.66

Table 11: Averages, per field, of the number of harvesting machines, periods with harvest operations, and hours worked per period.

we also observe a decline in the average number of harvesters operated across all scenarios as the value of  $\lambda$  grows. Specifically, solutions that favor cost containment ( $\lambda = 3$ ) require, on average, 20.1, 21.4, and 27.4 percent less harvest equipment in the AW, NS, and ES scenarios, respectively, compared to solutions that restrict the harvest time ( $\lambda = 1$ ). At the same time, the number of working hours in a field generally increases with the value of  $\lambda$ , leading to a longer harvest (on average, 50, 46.1, and 45.9 percent increased duration for  $\lambda = 3$  across the three scenarios as opposed to  $\lambda = 1$ ). These trade-offs are very important from a managerial perspective. When objective  $w_1$  (i.e., cost) is given more relevance, fewer harvesting machines are operated and higher preference is given to selecting more efficient machines. Since each harvester is operated, on average, for a longer time this strategy increases the risk of equipment failure. The opposite effect is observed when more emphasis is placed on objective  $w_2$  (i.e., time) because in this case the sugarcane is harvested more quickly and each machine is subjected



to less wear. However, this policy is more expensive. This analysis also explains the results given in Table 8.

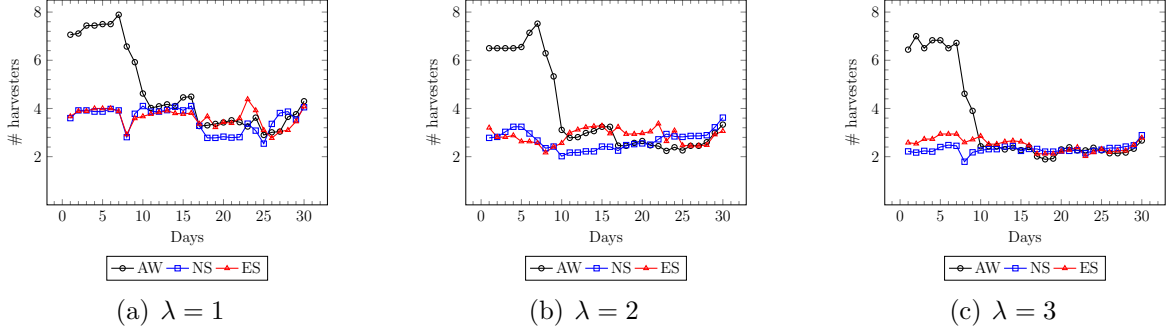


Figure 7: Average number of harvesting machines per field for instances with 30 fields.

Figure 7 highlights these findings for the large instances with 30 sugarcane fields. The average number of mechanical harvesters assigned to a field over the planning horizon is illustrated for the three Pareto-optimal solutions in each scenario. Bad weather conditions in the AW scenario greatly affect the harvest plan in the first week, since the reduced working hours available compel to deploy more harvest equipment in order to satisfy the demands at the mills. As shown in Table 10, both types of harvesting machines have to be used, despite harvesters of type 1 being less efficient than harvesters of type 2. For increasing  $\lambda$ , variations in the number of harvesting machines operated per period are less perceived as a result of the trade-offs discussed earlier. This analysis is complemented by Figure 8, which displays the average daily time worked in each sugarcane field for the same instances with  $|I| = 30$ . The weekend premium rates are reflected in the sharp reduction of the work time on Saturdays and Sundays, as expected. Otherwise, the daily work schedule does not show significant differences among the scenarios with the exception of the first week in the AW scenario. Finally, Figures 12–13 in Appendix B present further characteristics of the solutions obtained.

## 6 Conclusions

In this paper, we have addressed a tactical planning problem motivated by a Brazilian sugarcane milling company. The problem consists of developing a schedule for the deployment of harvest and transport equipment over a multi-period planning horizon so as to minimize the total cost incurred by the equipment used and the total time required to complete the harvest operations. Due to the conflicting nature of these goals, we have proposed a bi-objective

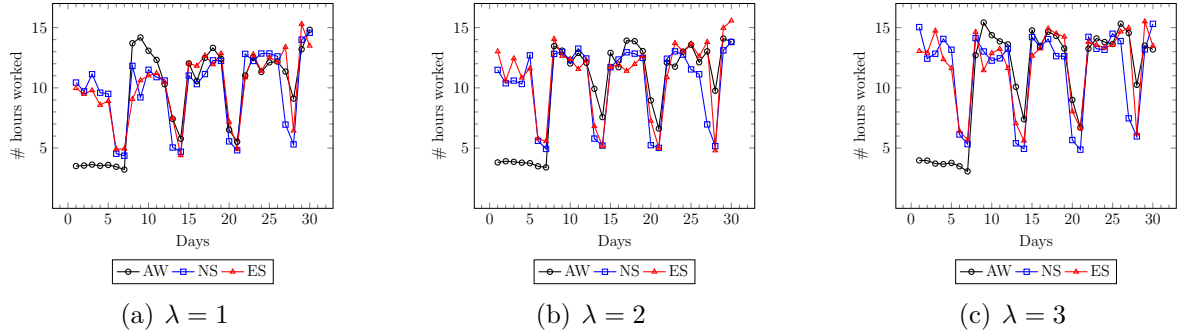


Figure 8: Average number of hours worked per field for instances with 30 fields.

mixed-integer program, which includes non-linear constraints and non-linear terms in one of the objective functions. By integrating the decisions on the deployment of harvest and transport resources into a single model, we allow for improved logistics coordination, as opposed to planning these operations separately, a practice that is generally followed at the tactical planning level. We have used linearization techniques to transform the original formulation into a computationally tractable bi-objective mixed-integer linear program. Pareto-optimal solutions are identified by the Progressive Bounded Constraint Method, which partitions the objective space into a sequence of non-overlapping subregions. Our extension of this method avoids the same Pareto-optimal solution to be returned while investigating two adjacent subregions.

We have performed a computational study on a set of semi-randomly generated instances that reflect the current harvest and transport practices at a milling company in the state of São Paulo (Brazil). The instances differ in the number of sugarcane fields that need to be harvested and the availability of the harvest machinery and road haulage vehicles over the planning horizon. The latter is impacted by the projected weather conditions and the work schedules in place on weekdays and weekends. Our comparative analysis of a subset of Pareto-optimal solutions identified within reasonable computing time has contributed to a better understanding of the trade-offs between cost performance and harvest efficiency. When the minimization of the equipment operating cost is favored, fewer mechanical harvesters are used that are operated for a longer time. This strategy leads to a longer harvest, higher machine maintenance effort, and as a result higher risk of equipment failure. By contrast, when more emphasis is given to minimizing the harvest duration, more harvesting machines are used but for a shorter time. As a result, the harvest operations can be completed faster at a higher cost and the harvest equipment is subjected to less wear. Furthermore, in all solutions obtained, preference is placed on using harvesters that have a larger capacity and therefore achieve more throughput in a

shorter time even though they are more expensive. In addition, vehicles with small transport capacity are favored to deliver the sugarcane to the processing facilities. These valuable insights allow decision makers to make informed value-adding decisions, thereby improving the overall performance of their harvest and transport operations.

Several further research opportunities can be identified. From a methodological viewpoint, the development of a specially tailored heuristic method to identify the set of Pareto-optimal solutions in reasonable computing time would be particularly useful for large problem instances. Moreover, our modeling framework could be extended to integrate further agricultural operations such as sowing and growing different sugarcane varieties as they also affect the determination of a schedule for harvesting and transporting the sugarcane. Another future research venue would be to examine our problem in a stochastic setting in order to explicitly account for different sources of uncertainty, e.g., weather conditions and crop yields.

## Appendix A: Data generation

In what follows, we denote by  $\mathcal{U}[a, b]$  the generation of random numbers over the range  $[a, b]$  according to a uniform distribution. Some parameters were drawn from a normal distribution with expected value  $\mu$  and standard deviation  $\sigma$ , expressed by  $\mathcal{N}(\mu, \sigma)$ . The parameters of the uniform and normal distributions were derived from historical data and discussions with our consulting partner, thus reflecting the real-life settings of harvest and transport logistics at a Brazilian milling company. All costs are given in Brazilian reals (R\$).

Parameter	Description	Unit	Value
$HT_i = \{a_i, \dots, b_i\}$	time window for harvesting field $i$		$a_i = [\mathcal{U}[1, 14]]$ ; $b_i = [\mathcal{U}[15, 30]]$
$A_i$	area of field $i$	ha	$\mathcal{N}(50, 10)$
$P_i$	productivity of field $i$	tonnes/ha	$\mathcal{N}(120, 20)$
$d_{jt}$	demand of mill $j$ in period $t$	tonne	$\mathcal{N}(2000, 100)$

Table 12: Generation of parameters related to sugarcane fields and demands of the mills.

## Appendix B. Supplementary results

Table 15 reports the objective values associated with the lexicographic solutions. The best values are highlighted in boldface. In spite of their limitations, since they reflect ‘extreme’

Parameter	Description	Unit	Type of harvester	
			$\ell = 1$	$\ell = 2$
Model type			Case A8810	John Deere CH570
$M_{\ell t}^{max}$	no. of machines		$[\mathcal{N}(15, 2)]$	$[\mathcal{N}(15, 2)]$
$Q_{\ell}$	capacity	tonnes/h	20	30
$mc_{\ell t}$	operating cost	R\$/h	200	230
$hm_t$	operator's wages	R\$/h	10 (weekdays), 15 (Saturdays), 20 (Sundays)	
$p_t^0$	moving cost between depot and a field	R\$/km	3.5 (weekdays), 5.25 (Saturdays), 7 (Sundays)	

Table 13: Generation of parameters related to mechanical harvesters.

Parameter	Description	Unit	Type of vehicle		
			$k = 1$	$k = 2$	$k = 3$
Model type			Volkswagen 31.280	Mercedes Benz 3344	Volvo FH-540
$V_{kt}^{max}$	no. of vehicles		$[\mathcal{N}(22, 2)]$	$[\mathcal{N}(22, 2)]$	$[\mathcal{N}(22, 2)]$
$C_k^{max}$	capacity	tonne	60	75	90
$s_k^e$	empty travel speed	km/h	70	70	70
$s_k^f$	loaded travel speed	km/h	60	50	40
$st_k$	service time	h	2	3	3.5
$p_{kt}$	transport cost	R\$/km	4	5	6
$hd_t$	driver's wages	R\$/h	16 (weekdays), 24 (Saturdays), 32 (Sundays)		

Table 14: Generation of parameters related to road haulage vehicles.

situations due to the predominance of one objective over the other, the lexicographic solutions facilitate the identification of the ideal values (columns 3 and 6). In turn, the deviation between the ideal values and the objective values of the Pareto-optimal solutions presented in Table 8 can be determined for the different scenarios. In this way, a decision maker is better informed of the maximum level of trade-off between the total cost and the total harvest time. For example, the solution obtained for the instance with 10 fields,  $\lambda = 1$ , and the AW scenario has a total cost (985,325 R\$) that is only 0.2 percent higher than the 'ideal' cost (983,396 R\$). However, the planned harvest duration (534.32 h) is 37.7 percent longer than the 'ideal' total harvest time (388 h).

Figures 9–11 illustrate the average proportion of mechanical harvesters available that are selected per period in each scenario and solution, according to type and number of sugarcane fields. As the maximum operating time available increases from the AW scenario to the ES scenario, more machines of both types are used. More harvest equipment needs to be deployed in the instances with 30 fields, as they also have the largest quantity of cane to be harvested.

I	Scenario	Left lexicographic solution ( $w_1 >_{\text{lex}} w_2$ )		Right lexicographic solution ( $w_2 >_{\text{lex}} w_1$ )	
		Total cost (R\$)	Total harvest time (h)	Total cost (R\$)	Total harvest time (h)
10	Adverse weather	983,396	1,123.19	987,381	<b>388.43</b>
	Normal schedule	<b>978,103</b>	1,253.23	987,554	413.25
	Extended schedule	981,989	1,189.66	991,288	458.11
20	Adverse weather	2,053,898	2,175.34	2,258,669	<b>1,798.42</b>
	Normal schedule	2,042,336	2,208.21	2,228,986	1,898.34
	Extended schedule	<b>2,039,556</b>	2,153.36	2,236,874	1,856.87
30	Adverse weather	<b>3,058,225</b>	3,228.88	3,102,598	<b>3,058.11</b>
	Normal schedule	3,066,998	3,694.03	3,119,587	3,066.65
	Extended schedule	3,060,552	3,593.27	3,100,885	3,107.36

Table 15: Objective values associated with the lexicographic solutions in the different scenarios.

In this case, nearly all the most efficient machines (i.e., type 2) are operated, while more than half of the harvesters of type 1 are used.

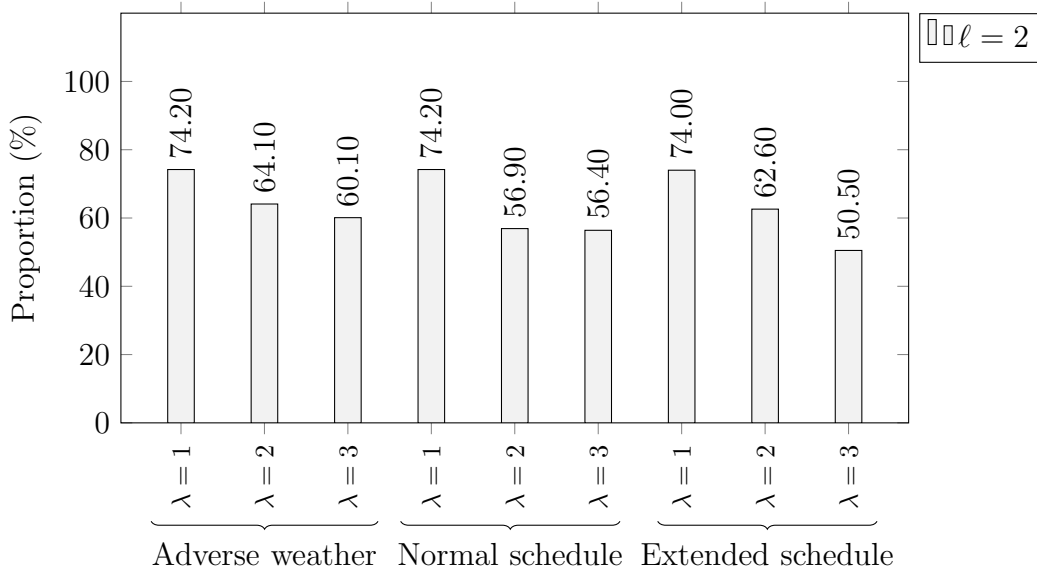


Figure 9: Average proportion of machines used per period for instances with 10 fields.

The average quantity of sugarcane harvested per hour is also a relevant performance measure, which is shown in Figure 12. The averages were calculated over all instances for a specific scenario. It can be seen that the harvest efficiency differs among the scenarios. However, there is a slight preference for solutions with  $\lambda = 2$  because they display a balance between the two objectives,  $w_1$  and  $w_2$ .

Finally, Figure 13 presents the harvest schedules of the three solutions identified under the

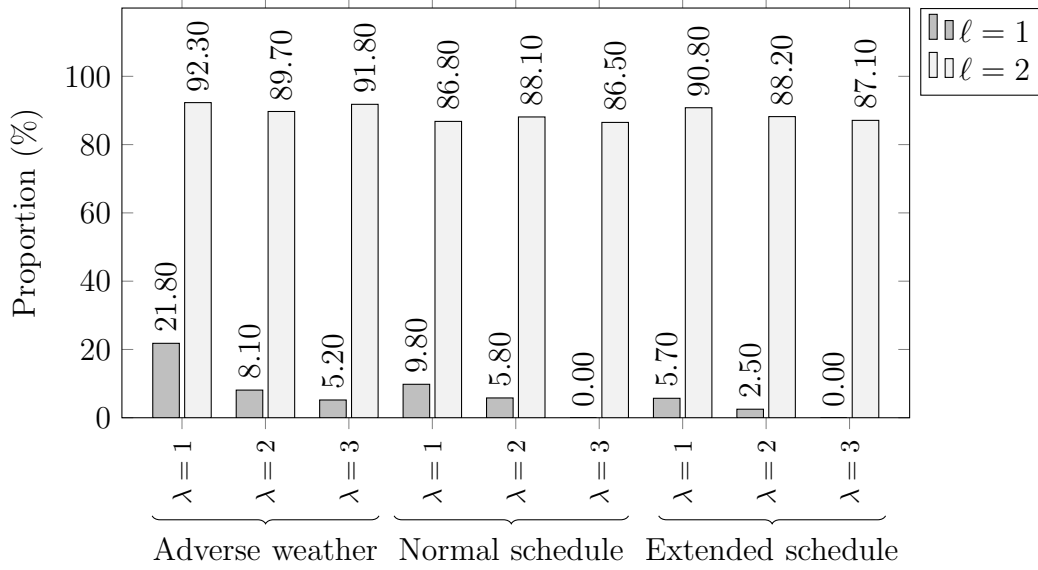


Figure 10: Average proportion of machines used per period for instances with 20 fields.

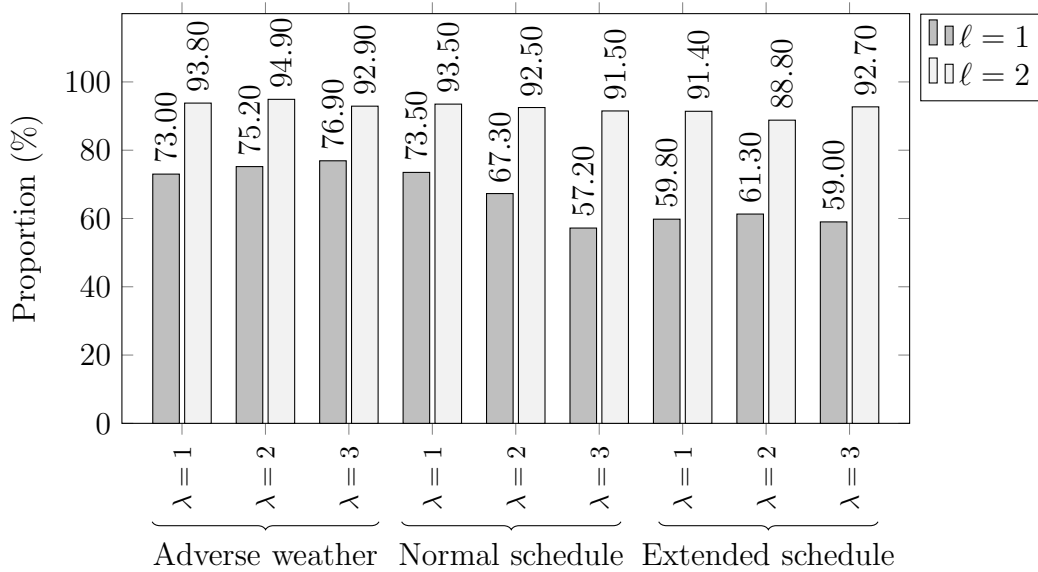


Figure 11: Average proportion of machines used per period for instances with 30 fields.

normal schedule scenario for  $|I| = 10$ . The numbers to the right of each bar show the average amount of hours worked daily on each field. The figure highlights the significant differences between the solutions and underlines the importance of adopting a multi-objective approach to the problem.

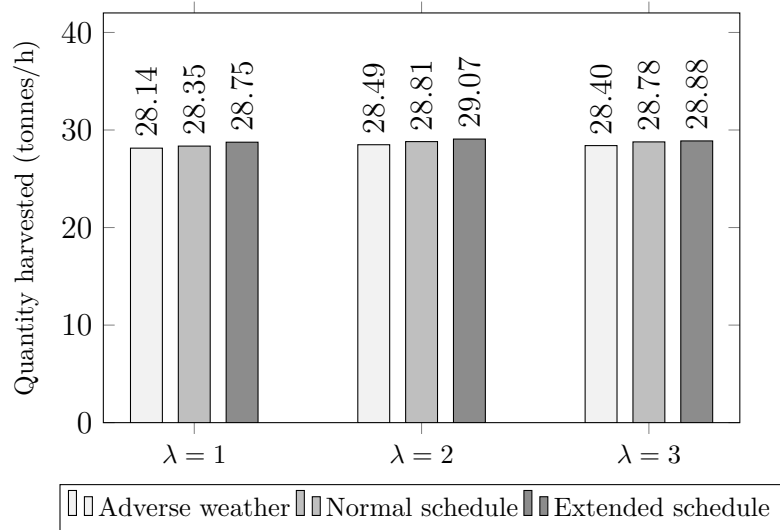


Figure 12: Average quantity of sugarcane harvested per hour.

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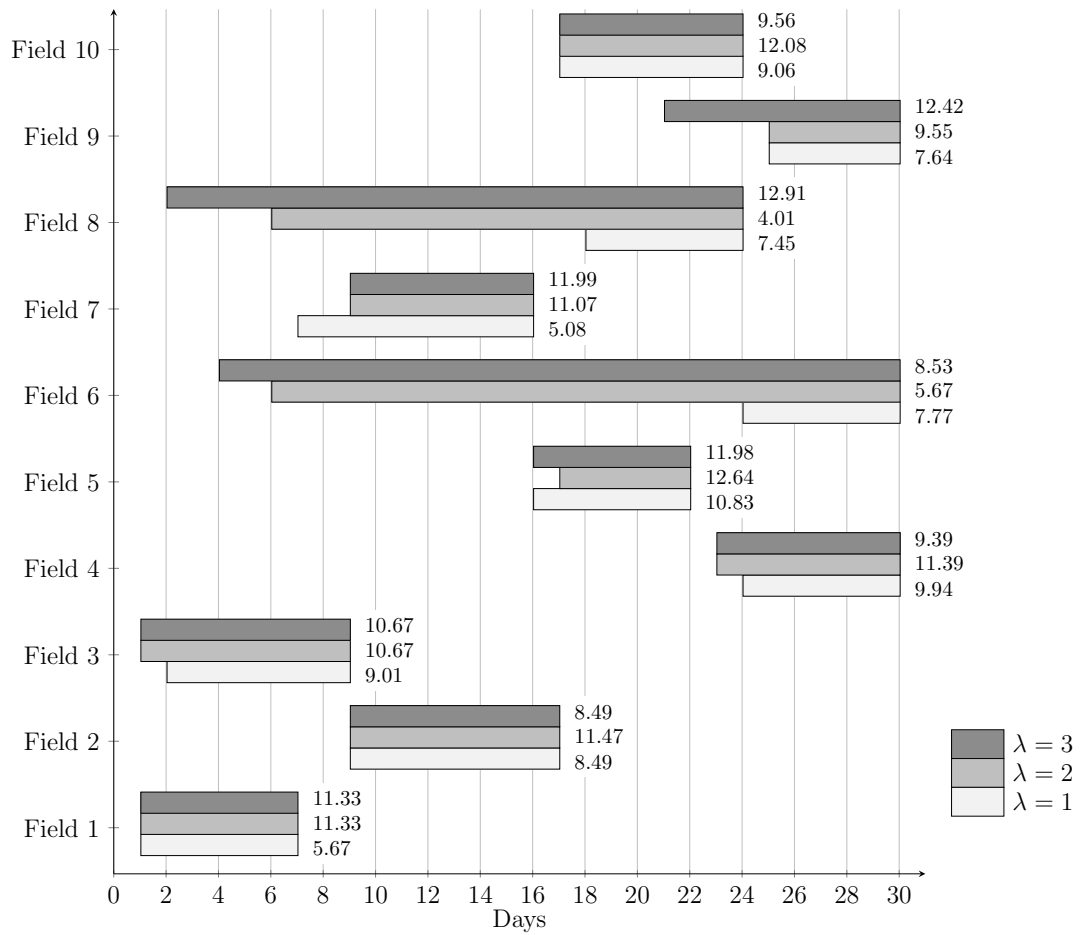


Figure 13: Harvest schedules associated with the Pareto-optimal solutions for the instance with 10 fields under the normal schedule scenario.



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